Available: DOI: https://doi.org/10.54117/gjpas.v2i1.29 Research article

Gadau Journal of Pure and Allied Sciences
Gadau J Pure Alli Sci, 2(1): 22-29 (2023)
ISSN: 2955-1722
DOI: https://doi.org/10.54117/gjpas.v2i1.29

An optimized stacking ensemble technique for creating prediction model of customer retention pattern in the banking sector

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Abstract

Banking is one of the sectors that pays close attention to their clients' behavior with a view to tracking their activities, most especially as relates to monetary transactions. To add new customers to the existing fold is not only time consuming, but also expensive. This is why Banks generally would like to do everything within their means to ensure the customer retention pattern is consistently high. The objective of this study, therefore, is to create a prediction model that is capable of predicting the retention rate of bank customers. In other to achieve this central goal, this study proposed a machine learning predictive model, created using a function that combines a number of base classifiers to produce an efficient model. The model was created from the dataset retrieved from an open repository, kaggle. The data basically comprised of some demographic and psychological features and the algorithms implemented on these datasets includes: KNN, CART and Naïve Bayes as base classifiers, while the Logistic Regression was used as the Meta Classifier. The model created was evaluated severally to determine its level of accuracy. The resulting output shows a very high accuracy of 83%. A further comparison of this result with the existing related studies unveils that, the proposed ensemble classifier out-performs the existing model which attains 79% to 81% classification accuracies. The proposed model is reliable and can therefore, be used as a bench-mark for similar models created for the prediction of customer retention pattern within the banking sector.

Article History

Received: 13/08/2022
Accepted: 08/11/2022
Published:10/04/2023

Keywords
Algorithm;
CART;
Classification;
KNN;
Model;
Prediction;
Regression

How to cite this paper: Oladimeji, O.M., Ajiboye, A.R., and Usman-Hamza, F.E. (2023). An optimized stacking ensemble technique for creating prediction model of customer retention pattern in the banking sector. *Gadau J Pure Alli Sci, 2(1): 22-29*. https://doi.org/10.54117/gjpas.v2i1.29.

1.0 Introduction

There is a glaring data explosion and great information resources in virtually everywhere in the world today; these data can easily be accessed using several tools. Mobile devices such as smartphones, tablets, etc. offers fast access to a variety of branded products and massive stored data. Customer expectations are shaped by sophisticated technology, convenience, price sensitivity, service quality, and socioeconomic variables reported by Hashim (2016). Customers frequently switch from one provider to another as a result of the abundance of options provided by improved technologies. This makes it difficult for businesses to keep old customers and attract new customers; such switching make businesses to record huge loss (Mahajan, 2015). Customer turnover has been emphasized in several recent studies, making it an important aspect of marketing management. For instance, a 1% improvement in retention rate has been demonstrated to boost the firm's worth by 5% on average (Gupta, 2015).

The customer churn projection reported in Yan (2014), is a severe concern for the banking business, with a massive influence on bankers' profit margins. As a result, a client retention policy can be targeted at high-risk customers who are considering switching to a competitor. Accurate and early identification of these categories of people is crucial to minimizing the expense that may need to be incurred by the bank sector's customer retention marketing program

Journal of the Faculty of Science, Bauchi State University Gadau, Nigeria
Computer Science and Information Technology

(Kaderabkora, 2015). Customer churning is the measurement or assessment of the total number of customers who switch to a competitor. It is the most common problem in any industry (Mishachandar, 2018).

The banking business in recent times pays greater attention to customer conduct and takes account of their behaviors. Making a new client to the bank is somewhat expensive in comparison to retention (Mishra and Rani, 2017). Researchers have shown interest in investigating the retention pattern of customers in recent years. The study reported by Mahmoud (2019) adopted a survey approach to gathering of the research data in his proposed study. Having high retention of bank customers is beneficial and required for sustainability of bank growth. Some banks have realized this and have come up with a number of marketing strategies, especially the use of technologies.. Bank customers are capable of boosting the bank‘s image, just as businesses can boost their profits by working with their customers. As a result, existing customers must be retained, which can only be done by understanding the client's concerns about switching banks. A customer attrition plan can be targeted at high-risk customers who wish to cease conducting operations with you and go to a rival. Accurate and early identification of these consumers is crucial to minimizing the expense of the bank sector's customer retention marketing program (Kaderabkora, 2015).

In recent times, machine learning is used in the financial sector to measure performance in a variety of ways. The technique considers the fund performance analysis, create relevant models and evaluates such model to determine its consistency in accuracy. Traditional model evaluation methods, such as the modification and optimization of specific stocks' unique risks, a study of probable laws, and the prediction of revisions to the risk model and fund performance evaluation technique, can be improved using associated technologies Fund’s short-term exposure (Galagedera, 2014).

A number of studies have focused on forecasting churn using the random forests method. For instance, in the study reported by Burez (2013), the study implements three different methods for churn prediction: sampling approaches, gradient boosting, and weighted random forests. The weighted random forest method was shown to be the best algorithm among the three. Also, the study reported in Xie (2014), introduced improved balanced random forests (IBRF), which combined sampling methodology with cost-sensitive learning strategies, and the results demonstrated that IBRF outperformed ANN, decision trees, and SVM algorithm. Further research in this direction shows the use of random forests method to predict churn. The use of the weighted random forest method gives the much better results.

Although, previous studies have employed a range of data mining methods to anticipate customer turnover, there is still no clear conclusion on the application effect, as these models is still not in its optimal performance, there is still need for improvement. This is one of the reasons for implementing a much better approach in this study, with a view to achieving an improved predictive model.

Ensemble Machine Learning (ML) technique appears to be one of the possible ways to achieve an optimal model, this study is therefore, looking at such promising direction. The Ensemble ML theory has a lengthy history (Rokach, 2015); the concept of Ensemble methods uses a combination of strategies to allow many machine-learning models, known as base learners, to combine their predictive strength that is capable of producing an optimal prediction. Ensembles are intended to address two issues: bias and variance, as well as their interactions. The objective of this study, therefore, is to propose the use of data scaling and a stack ensemble technique to increase the predictive accuracy of customer retention rate in a banking system.

The rest of this paper is organized as follows: In the next section, there is a brief discussion on various forms of learning. In Section 3, a number of literature that is related to the current study is reviewed. Section 4 discusses the material used and several data mining techniques implemented in this study. The performance of the models emanated from this study is evaluated, graphically represented and discussed in Section 5. This study concludes in Section 6.

2.0 Forms of learning

Learning is important during training of data, it basically takes two forms, supervised and unsupervised learning as illustrated in Figure 1. In supervised learning, the training data are composed of input-output pairs. A learning algorithm such as back propagation in practice, tries to find a function which when given the inputs, produces the outputs. Unsupervised learning is where the system has input data but no example outcomes are provided to aid learning. Such machine is fed with the basic data and must learn more about the data to establish an outcome. Clustering algorithm and Association rule are well-known and typical of unsupervised learning approaches. In other words, unsupervised learning does not use labels and the algorithms are left to discover and learn on their own. Through the repeated application of training data, the network approximates a function of the input domain. There are two main types of neural networks: fixed otherwise referred to as non-adaptive, and dynamic known as adaptive.

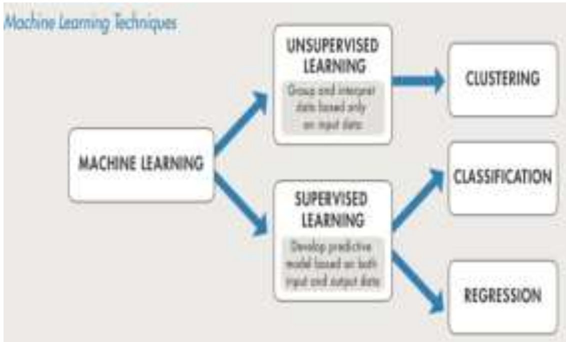

Figure 1. Machine learning techniques-unsupervised and supervised

The concept of machine learning is very crucial in Artificial Intelligence (AI). Learning usually occurs in a dataset by discovering and gaining more understanding of the relationship in the dataset. This enables judgements to be made based on certain clearly stated rules. Machine learning is used when a difficult problem or activity necessitates the use of the huge volume of data. It is a smart choice for more complicated data because it produces faster, and more accurate results than using any other conventional methods. It is useful in many ways, including assisting a company to find both profitable opportunities and unexpected threats (Sayed *et al*., 2018). Other common forms of learning are Instance Based and Ensemble Learning**.**

Instance-based learning is a memory-based learning in which the instances are labelled according to the previous instances stored in the memory. The K-Nearest Neighbour (KNN) technique, for instance, is one of the most widely used instance-based machine learning algorithm suitable for classification. KNN does not attempt to build an internal representation, and simulations are not carried out until the classifying period is concluded. In the feature space, KNN keeps just duplicates of the training data, or an instance's classifier is dictated by a bigger percentage of its neighbours. The calculated distances are used to identify and classify a group of training instances (k) which are the closest to the new site. In spite of the fact that it is simple; KNN has been used in a variety of applications. In the course of exploring client churn dataset, KNN is useful in the determination of client attributes in relation to other customers in each class as reported in (Keramatia *et al*., 2018).

Ensemble-based learning on the other hand, integrates the results of several classifiers to make predictions. Bagging methods (such as Random Forest and logistic regression) and boosting methods are typical examples of ensemble learners (such as Ada Boost, stochastic gradient boosting).

3.0 Review of related literature

This section reviews some literature with respect to the prediction model building using machine learning approaches. It also discusses the relationship that exists between the organizations vis-a-vis their customers. Understanding the concept of consumer churn may be very critical in any business. Different marketplace domain names have a few comparable elements just like the fee provided to the consumer, the perquisites supplied, the length of time the customer is associated with the company, just to list a few. Data evaluation has been used in previous works to recognize customer behaviors using regression models. Clustering has been employed in certain research works to class consumer corporations into groups with similar tendencies, such as the study on customer churn prediction in telecommunication using Data Mining Techniques reported in (Asgari *et al*., 2019). The study revealed how the consumer turnover can be predicted based on a number of predictive attributes. Businesses can take the required efforts to retain clients by conducting research into such behaviours.

A research study reported by AlKurdia *et al*. (2020), reveals how the employee retention and organizational performance is capable of affecting the customer retention in the banking industry. In most cases, bank customers may decide to seek for services where their preferred bank's employee secure another job. There is a need to address the problem of attrition as regards both bank's customer and employee. Customer attrition is the process of a customer switching from one business service to another. Customer Churn is a technique for detecting potential churners before they leave a firm. This step aids the organization in designing appropriate retention measures to attract and retain potential churners and therefore, lowering the company's financial loss (Umayaparvathi and Iyakutti, 2020). Customer turnover is a concern in a variety of industries, but it is more noticeable in highly competitive businesses. Losing clients results in financial loss due to lower sales, as well as an increased need to recruit new consumers (Guo-en and Wei-dong, 2018).

The goal of customer downtime forecasting is to anticipate upcoming events that are based on information specific to each network subscriber and a predetermined forecast horizon. According to Umayaparvathi and Iyakutti (2020), the learning phase, the testing phase, and the prediction phase organization are the three phases of the customer churn prediction problem. Telecommunications service provider's historical records, such as call records or logs, and corporate or personal client data, contribute to the customer churn problem throughout the training period.

The training set with the highest accuracy was evaluated in the test stage to forecast unsubscribe records from an actual data set without any unsubscribe labels. Finally, during the prediction phase, the problem is classified or predicted. The concept of predictive mining is sometimes referred to as knowledge in the discovery phase. Anticipating customer interaction helps to avoid customer relationship management (CRM) crisis, especially for consumers opting out in the future by attracting possible unsubscribes with improved service and retention policy offers or packages. Therefore, loss of business income can be avoided (Umayaparvathi and Iyakutti, 2020; Shaaban et al. (2015). According to these researchers, churners are divided into two categories: involuntary and voluntary.

Chih *et al*. (2020) employed a convolutional neural network technique to anticipate customer attrition rates in a CRM dataset provided by US telecommunication carriers. They combined two different neural network approaches, such as pervasive ANNs and self-organizing maps, to construct two hybrid models to forecast churn rate (SOMs). ANN, coupled with ANN (ANN + ANN) and SOM combined with ANN (SOM + ANN) is the hybrid models. The principal strategy of the two-hybrid styles, which filters out unrepresentative schooling data, is in charge of the information discount mission. The results of the previous stage are then employed in the second technique to develop a prediction model. Three different types of testing sets are employed to check the performance of these models: basic testing set and fuzzy testing sets based on filtered-out data utilizing the first method of two hybrid models, such as ANN and SOM. The combined model exceeds the basic single neural network model in terms of prediction accuracy, with the ANN + ANN combined model exceeding the SOM + ANN hybrid model in particular.

In the study reported by Oyeniyi and Adeyemo, (2015), the duo observed through their study that, the customer-centric banking business, client churn has become a big issue, and banks have attempted to monitor customer interactions for warning signals of customer behavior, such as decreasing transactions and inactive accounts. The study further works on analyzing client churn in the banking business, creating models with KMeans, and iterative incremental pruning to achieve error reduction using a *JRip* method in Weka. The data explored were retrieved from the customer service management database and transactional warehouse of a prominent Nigerian bank. The data show client activity patterns and help the bank spot customers who are about to unsubscribe.

Also, in other to increase the forecasting capabilities of various machine-learning approaches, Guo-en and Wei-dong (2018) explored the use of Support Vector Machines (SVM) on structural risk reduction to churn prediction analysis. Attempt to compare the results of using SVM with other machine learning techniques such as: artificial neural networks, decision trees, and logistic regression. The evaluation results showed that, SVM has the highest accuracy, success rate and coverage rate.

A much related study by Benlan and Yong (2018), proposed a strategy for predicting customer attrition based on the SVM model. In the study, Random sampling was utilized to develop the SVM model based on a number of customer's characteristics. In dimensional or indefinite space, the support vector machine creates a hyperplane that would be utilized for classification. The use of random sampling can be employed to change data distribution and in practice, this generally reduces the data collection imbalance.

4.0 Material and methods

The experimental framework of this study is stated in sequential steps with a view to achieving the objectives of this study. The general objective of this study focuses on modelling an optimized stacking ensemble method for predicting the customer's retention pattern in a banking system. The study followed the following steps:

4.1 Data collection

The data used for the creation of prediction models in the course of this study were retrieved from an open repository called Kaggle. The retrieved dataset is imported into the editor for processing using the *pandas* library. The processing is inevitable to make it acceptable to the algorithms implemented on it. Preprocessing essentially helps to remove outliers and inconsistencies in the dataset. The dataset has a number of attributes, however, not all the attributes are relevant for prediction purposes. Some of the attributes that plays a good indicator of customer churn in the dataset include: *Credit_score, Geographical location, Age, Tenure, Estimated salary, HasCrCard, IsActiveMember*. Since there are other attributes noy listed here that seem to be irrelevant for prediction purposes, but found in the dataset; preprocessing becomes very essential to select only the useful features.

4.2 Feature selection

This is otherwise known as feature engineering. It is a fundamental method of selecting and deciding which of the attributes are best or most proper for predictions (Hadden *et al.*, 2018). The importance of this stage in predicting client loss cannot be over-emphasized. Feature engineering is the process of picking a subset of features. In data mining, this is a well-known and widely used dimensionality reduction approach of picking the most relevant among the attributes in a dataset.

Previous studies have shown the use of several techniques to reduce the size of attributes in a dataset. For instance, In one of their investigations, Khan *et al*. (2015), employed a t-test to see how well a single feature could distinguish between people who had stirred and those who hadn't. For feature selection, a tree-based technique was applied. For constructing a list of connected predictors, this strategy performed effectively. The approach used search strategy to peruse the given dataset and divide the feature selection into two groups.

The model combined and stacked three base-classifiers to formulate the stack ensemble model. The base classifiers were first used individually for the prediction of bank customers churn dataset and each resulting output emanated is evaluated to determine the individual performance. This was later compared to the results gotten from the stack ensemble model which was a stack of the base classifiers (KNN, CART and Naïve Bayes) as well as the MetaClassifier (Logistic Regression).

This study, therefore, takes four different case-approaches to draw a conclusive comparative study, Case A: uses a reduced dataset with KNN; Case B uses a reduced dataset with CART; Case C: uses reduced dataset with Naïve Bayes; and Case D: uses a reduced dataset with Stack Ensemble Model.

The implemented system elaborated a stepwise approach of data mining to solving the prediction of customer churn. The process initiated dataset collected from an online data science tool and data repository *Kaggle*; secondly, the filtering of data was achieved and the normalization which helps to remove outliers and inconsistencies in the data; and thirdly, the Chi-Square feature selection was conducted for selection of the optimal subset solution from the dataset. The reduced dataset from the feature selection technique now formed a new data entry to the classifiers used. The source data were divided into two: training set and testing set. The division arrived at a percentage ratio of 75% for training and 25% for testing. This was achieved through the *sklearn.model_selection* from which the *train_test_split* was imported and passed to our classifiers under consideration.

The use of *scikit_learn* helps the model building in this study, while the metrics computed to evaluate the performance of the model created was made possible through the use of *sklearn* library from where metrics were imported. *Scikit_* learn is a Python library that contains several tools required for fitting model from dataset. *Scikit_learn* has features that include: KNN, Random forest, SVM, etc. These features make *scikit_learn* tools to be very suitable for building ML models and hence, maximally explored in this study. Figure 2 illustrates feature selection approaches.

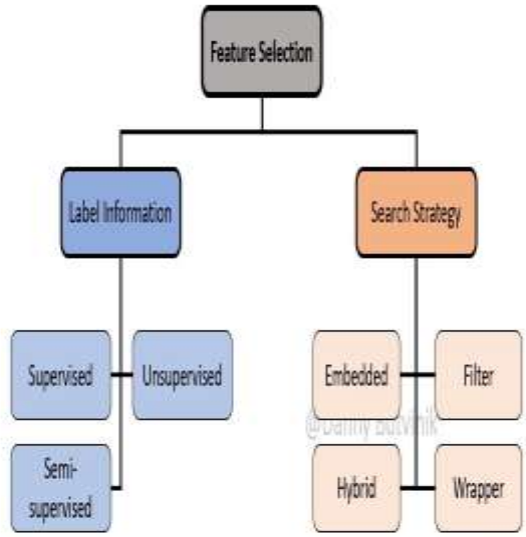

Figure 2. Feature selection approaches adapted from Butvinik (2009)

The proposed system is also designed to compensate for dataset imbalance using a random sampling approach. Other approaches used employs a filter selection technique to select the optimal subset from the dataset using the *Kbest* algorithm. The dataset is divided into two parts: a training set; based on the specific percentage ratio of 75% and testing set of 25%..

The training set is fed to the base classifiers individually (KNN, CART, and Naive Bayes), as well as the *MetaClassifier* (Logistic Regression), which results to a new model through the training of the combined predictions from previously trained models on the same dataset as shown in the study framework illustrated in Figure 3. The remaining 25% is used to evaluate the trained model's performance. Machine learning statistical variables, classification accuracy, true positive rate, false-negative rate, error rate, specificity, sensitivity, and training duration were used to analyze the outcomes. The receiver operator characteristics to further buttress the accurate result.

The developed predictive model was evaluated based on the following metrics and the graphical representation in respect of each metric is illustrated in the next Section. Table 1 shows the formula used for the computations.

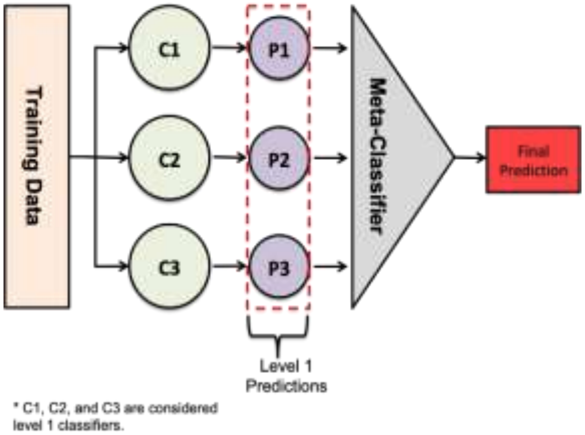

Figure 3. Schematic structure of a classifier framework

Table 1. Formula for metric computations

Measure	Formula
Accuracy (recognition rate)	TP + TN / P + N
Error rate (Misclassification rate)	FP + FN / P + N
Sensitivity (True positive rate)	TP / P
Specificity (True negative rate)	TN / N

In relation to region, TP represent True Positive, TN represent True Nagative, FP represent False Positive, P represent Positive, and N represent Negative.

5.0 Results and discussion

This section presents the results of exploring customer's churn dataset using machine-learning approaches. Experiments were designed and implemented to improve bank churn prediction model using the stack ensemble method. The main motive was to come up with a highly accurate predictive model. The model was achieved based on some coding implementation in Python, specifically in the Jupiter Notebook platform to create a friendly user experience. The accuracy of the model constructed based on KNN, CART, NAÏVE Bayes and STACK Ensemble is represented in Figure 4. Apart from accuracy, another measurement determined for the model created is specificity and sensitivity. Naïve Bayes which is based on probability distribution has the highest specificity and the most sensitive on a scale of 0 to 1 as shown in Figure 5. Also, considering the time it takes to train the dataset using each technique, it can be inferred that, it takes KNN few seconds to converge, while it takes the stack ensemble the longest time to converge as represented in Figure 6. In order to determine the ROC, the graph of the true positive and false positive rate were plotted for models created using KNN, Naïve Bayes and Stack Ensemble as represented in Figures 7, 8 and 9 respectively.

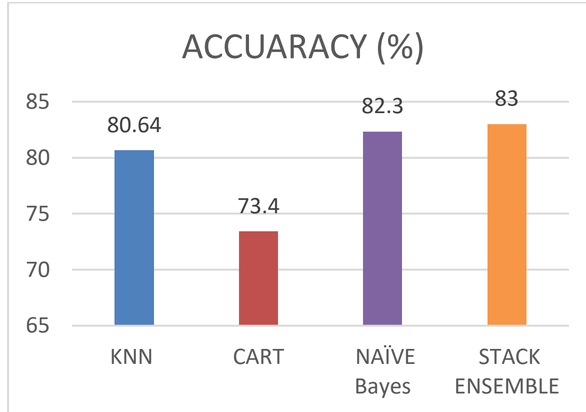

Figure 4. Classification Accuracy for the implemented techniques

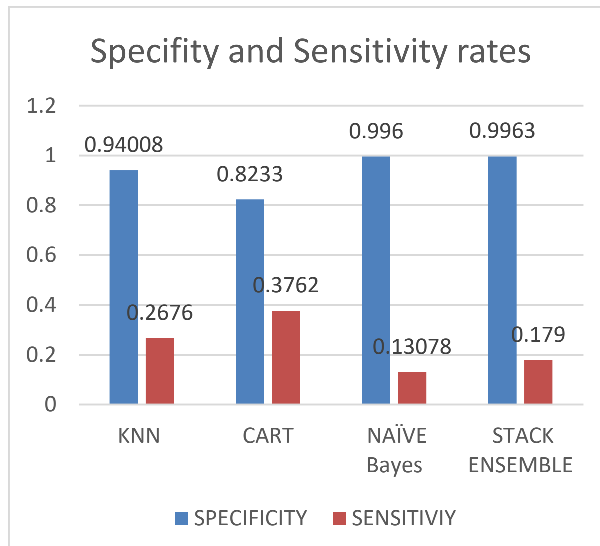

Figure 5. Sensitivity and Specificity Chart for filter Approach

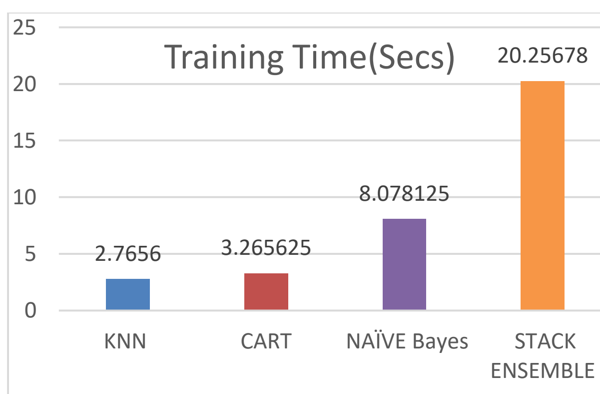

Figure 6. Training Time obtained for the four case-models used

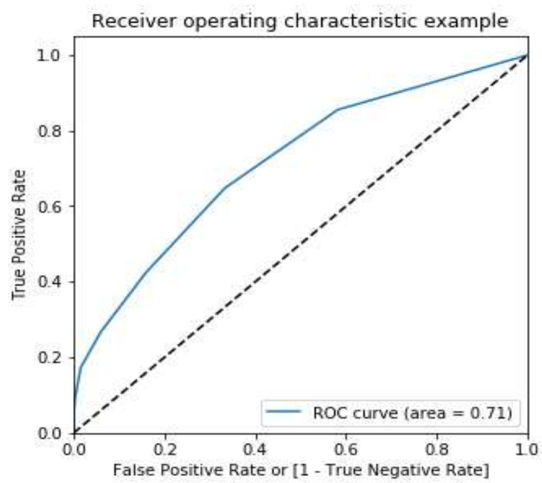

Figure 7. KNN ROC

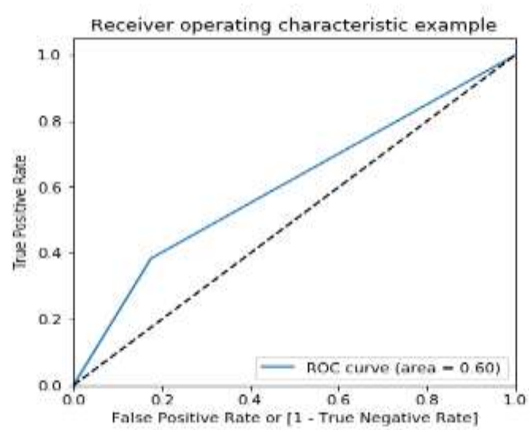

Figure 8. CART Model ROC

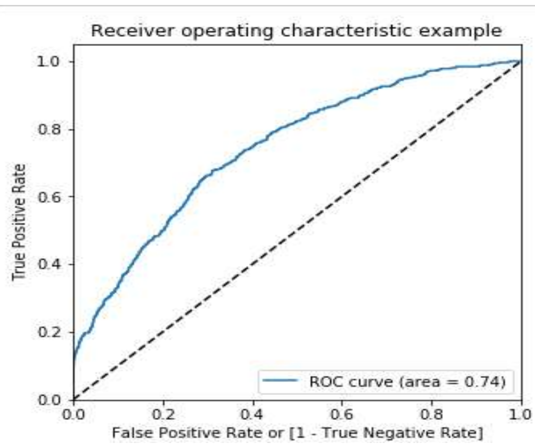

Figure 9. Stack Ensemble ROC

6.0 Conclusion

This Section concludes this study. A prediction model of the customer's retention pattern created from customer churn dataset retrieved from *kaggle* in an open repository. The dataset is explored using a number of libraries in python. The model created was carefully evaluated to determine its accuracy, sensitivity, error rate and specificity.

One of the reasons for determining the customer retention pattern is to enhance the policy making of the organization. It would also make an organization to be more focused on bulk of variables that are good indicators and very relevant in the determination of how customers may want to switch. It helps to know what is being done right and it is capable of unveiling areas that need urgent improvement. High retention rate is the most desirable of any organization, while low attrition rate is a good signal that indicate an organization is doing well. No organization wishes to record the high attrition rate or low retention pattern. The prediction model created was based on a number of attributes as earlier discussed.

Findings from this study shows that, a number of attributes such as: credit score, geographical location, age, tenure, salary and the status of activeness of a customer, determines to a large extent the decision that could be taken by such customers whether to stay or leave the bank. Also, researchers and practitioners could adopt the use of Stacking Ensemble Technique in lieu of the conventional methodology for optimal performance of the fitting predictive model from churn dataset. Evaluation of the prediction model created in this study reveals an accuracy that is high, it is therefore, reliable for prediction of customers' retention rate in the Banking Sector.

Declarations

Ethics approval and consent to participate

Not Applicable

Consent for publication

All authors have read and consented to the submission of the manuscript.

Availability of data and material

Not Applicable.

Competing interests

All authors declare no competing interests.

Funding

There was no funding for the current report.

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