A PREDICTIVE STRUCTURE FOR DETERMINING THE LIKELIHOOD OF AN USER CHURNING IS BEING CREATED

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ABSTRACT

Churn prediction is a typical use case in the field of machine learning. Churn, for those of you who are unfamiliar, is the business equivalent of leaving. It is crucial for telco companies to understand the causes of and triggers for customer churn. Businesses can take the required measures and activities to stop consumers from leaving by using an accurate and reliable churn prediction model.

Churn prediction is recognizing customers who are most probable to cancel their membership to a service based on how they use it. In order to reduce customer turnover and develop strategies to win back lost customers, numerous firms will benefit from understanding the causes of customer churn and the actual rate of customer churn using the information provided in this paper.

This study makes use of the logistic ID3 decision tree, support vector machine, and ANN machine learning methods. The dataset used for this study is referred to as churn modelling. The Kaggle website hosted the dataset. To identify an acceptable model with greater accuracy, the results are compared. As a result, the Random Forest method outperformed other algorithms in terms of accuracy. And precision was around 87%. The Decision tree algorithm had the lowest accuracy, coming in at 78.59%.

INTRODUCTION

The percentage of customers that ceased using a given company's product or service during a specific phase of time is recognized as customer churn. By dividing the number of clients the company lost during that time period by the number of customers it had earlier, prior to that time period, one can determine the churn rate. Predicting client turnover is a difficult endeavour, but it is also crucial for business reasons, particularly in areas like technology, telecom, finance, etc. where managing the cost of customer acquisition is expensive and challenging. Predicting a customer's impending churn while there is still time to take action could result in a significant boost in additional revenue for businesses.

Churn prediction involves figuring out which consumers are about to stop using a service or purchasing a product. The difficulty of binary categorization also applies to forecasting client attrition. Each period, customers either churn or stay. There are two categories of consumer churn: "accidental and intentional." Accidental churn occurs when circumstances change to prevent customers from using the services later, for as when economic circumstances make advantages prohibitively expensive for the customer. Intentional churn occurs when customers leave one company in favor of another that offers the same services, but with better suggestions from competitors, more advanced services, and lower prices.

Churn prediction has grown in importance for the telecom industry in recent years. to reduce the rate of customer attrition. The telecom carriers must identify these clients before they churn in order to address this issue. Therefore, it is crucial to create a distinct and precise classifier that can forecast future churns. This classifier needs to be able to identify users who are possible to go away soon so that the operator is able to take any essential action to keep them from leaving, such as offering discounts and promotions or utilizing another tactic.

A crucial indicator of client happiness is the churn rate. High turnover rates indicate clients are leaving you, whereas low churn rates indicate satisfied customers.
A modest monthly/quarterly churn rate builds up over time. A 1% monthly turnover rate quickly increases to almost 12% annually. We are using the Kaggle-available "Telecom Customer Churn" dataset for our research. For 7043 clients, there are 22 characteristics or independent variables and 1 dependent variable. Dependent or labelled variables show whether a consumer has left the business recently (churn=yes). This is a binary classification problem since the dependent variable only has two possible states: yes or no, or 1/0.

LITERATURE SURVEY

The study of customer turnover in banking covers a lot of ground. One of these researches [7] uses an SVM model to forecast client attrition at commercial banks. A consumer dataset from a Chinese commercial bank with 50,000 customer records has been used for this study. During attendance are ultimately 46,406 valid data records after preprocessing the records. SVM models with radial basis kernel function and linear SVM are the two types that were chosen. The under-sampling strategy significantly increased the forecast power of the categorization models. The SVM model and even the general assessment parameters are unable to determine the prediction potential of the model unpaid to the imbalanced skin texture of the definite commercial bank client turnover dataset.
The findings show that combining an SVM model using a random sampling technique can greatly increase predictive power and help commercial banks make more precise churner predictions. However, in the present research, there were 1:10 more churners than non-churners. The outcome in 1:1 is rising as high as 80.84%. This is the work's primary flaw. An added study [8] presents a scholarly analysis of the employ of data mining to retrieve information from banking industry sources. According to the research, consumers who employ added financial services (products) appear to be more loyal, allowing the bank to focus on clients who use less than three products and market to them according to their needs. the utilised database
The study is based on a neural network method of churn prediction found in the Alyuda NeuroIntelligence programmed that separates the data keen on three sets: the training set, the justification set, and the testing set. The features that to decline, the distinctiveness that need, and the goal distinctiveness to be deliberated are the three types of characteristics that are discussed throughout the data analysis stage The network design process's hidden layers are selected by the model. The results of the network's training show that the CCR% of validation is 93,959732. The analysis came to the conclusion that the bank provides extremely well-tailored programmes for retirees and that there is very little chance of competition given the high percentage of retirees among the overall amount of clients (691/1886).
The standard measure known as Area Under Curve (AUC) is worn to evaluate the model's effectiveness. The telecom operator Syriatel contributed the dataset that was used in the study. Decision Tree, Gradient Boosted Machine Tree (GBM), and Extreme Gradient Boosting (XGBOOST) are the four approaches the model has used. The big data platform was decided upon as being the Hortonworks Data Platform (HDP). Approximately all stages of the goods development, including data investigation, function progress, training, and software testing, utilised Spark engines. K-fold cross-validation was used to optimize the method hyper-parameters. The illustration for learning is rebalanced by captivating a illustration of data to balance the two classes because the target class is unbalanced. the churn class was multiplied in the study's initial oversampling in order to fit with the other class

EXISTING SYSTEM

One of the key and most typical problems in game analytics is predicting player behaviour and customer attrition. Feature engineering is a critical phase in creating a customer churn prediction model. Features are frequently created in the mobile game industry using unprocessed behavioural telemetry data, which presents difficulties in creating relevant skin tone and clear feature frameworks. By merging data on user Lifetime, Intensity, and Rewards (RFMLIR), this study suggests an improved Recency, Frequency, and Monetary value (RFM) feature architecture for churn prediction in the mobile gaming industry.

The establishment of both univariate and multivariate churn models for prediction, the employing of robust exploratory techniques, and the analysis of behavioral variations among churners and non-churners inside the given structure for various churn explanations and definition groups all contribute to validating the suggested structure. Even if feature relevance varies between churn definitions, the long term frequency characteristic stands out as being the majority of the significant one. The top five variables that the multivariable churn prediction models employ to distinguish themselves from one another are long- and short-term frequency characteristics, monetary, intensity, and longevity.

PROPOSED SYSTEM

The proposed method is to build a BANK CUSTOMER CHURN Prediction using Machine learning Technique. We are going to develop an AI based model, we need data to train our model. We can use BANK CUSTOMER Dataset in order to train the model. To use this dataset, we need to understand what the intents that we are going to train are. An objective is the purpose for which a user interacts therewith a predictive model or the purpose for which each piece of data that a certain user provides to the model is provided. Those objectives may differ amongst solutions depending on the domain for which you are designing an AI solution. The plan is to create training samples for each intention define various intents, and then train your AI model using the intents as training categories and the sample of training data as models training data. To use different Algorithm, we can get a better AI model and best accuracy. After building a model we evaluate the model using different metrics like confusion metrics, precision , recall, sensitivity and F1 score.

ARCHITECTURE OF PROPOSED SYSTEM

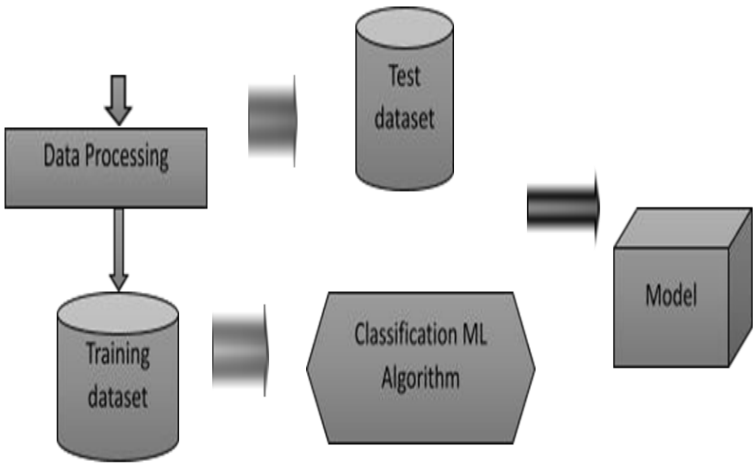

Fig.1. Customer churn forecasting structural design

SYSTEM ARCHITECTURE

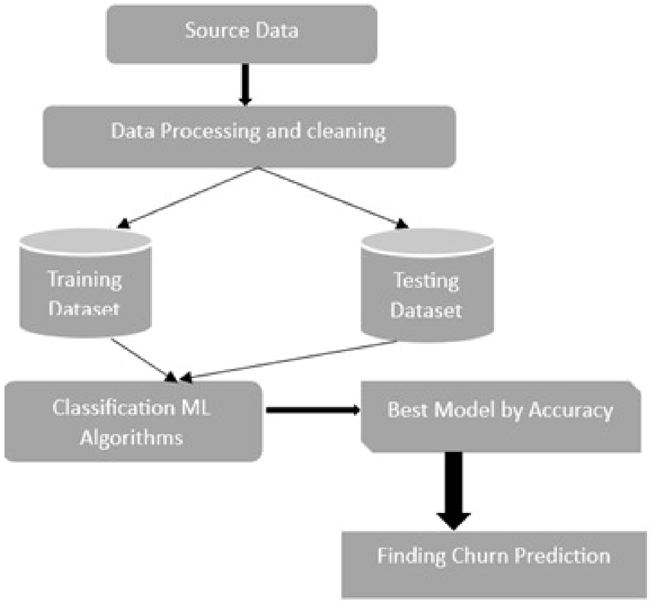

Fig.2. Block diagram of machine learning-based customer churn prediction in banking

DEFINE PROBLEM

Our goal is to create a project that will assist businesses in determining whether or not their consumers will churn. These initiatives will aid businesses in correctly and speedily predicting client turnover rates. These forecasts will take into account a number of crucial variables, like gender, internet safety, streaming services, tech assistance, etc.

1. Data Collection:

Gather relevant data about the customers, including historical customer information, transactional data, demographic details, and any other data points that might be indicative of churn.

2. Data Preprocessing:

The gathered data should be cleaned and prepared. In this phase, missing values are handled, outliers are eliminated, numerical features are normalized or standardized, and categories are encoded.

3. Feature Engineering:

Create new features or transform existing ones to enhance the predictive power of the model. For example, you might calculate metrics like customer tenure, average transaction amount, or frequency of interactions.

4. Feature Selection:

Identify the most relevant features that have a strong correlation with customer churn. This process helps reduce dimensionality and eliminate noise in the data, improving model performance and interpretability.

5. Model Selection:

prefer an suitable machine learning algorithm that suit the trouble at hand. Commonly used algorithms for churn prediction include logistic regression, decision trees, random forests, gradient boosting, and neural networks.

6. Training and Validation:

divide the data keen on training and validation sets. Employ the training set to train the churn prediction model and the validation set to assess its performance and fine-tune the model.

7. Model Evaluation:
Evaluate the presentation of the churn prediction model by means of relevant metrics for example precision, precision, recall, F1 score, and receiver operating characteristic (ROC) curve analysis.
8. Churn Probability Calculation:
Calculate the churn probability for each customer using the trained model. This probability represents the likelihood of a customer churning within a specified timeframe.
9. Customer Segmentation:
Group customers based on their churn probability and other relevant characteristics. This segmentation helps businesses tailor retention strategies for different customer segments.
10. Actionable Insights:
Provide actionable insights and recommendations based on the churn prediction results. This could include identifying high-value customers at risk of churn, suggesting personalized for improving customer experience.
11. Monitoring and Updating:
constantly check the presentation of the churn prediction model and update it periodically as new data becomes available. This ensures the model remains accurate and reliable over time.

IMPLEMENTATION

The many studies that have been conducted to forecast customer attrition are described in this section. Models for machine learning are included. The authors have added data from numerous sources in addition to the traditional data used for forecasting customer turnover. It comprises information about phone conversations with clients, websites and things they have looked at, interactive voice data, and other financial data. It uses a binary classification technique to forecast client attrition.

Despite the fact that this model shows a significant improvement, the data it was built on is never easily accessible. Churn prediction is a binary classification problem, and according to the authors, there is no reliable way to gauge how confident the classifier used for churn prediction is based on the studies that have been conducted. Additionally, it has been noted that the classifiers' accuracy varies depending on which zones of the dataset they are applied to.

Scikit-learn:
Scikit-learn is a popular Python library for machine learning. It provides a wide range of algorithms for classification, regression, and clustering tasks. Scikit-learn offers tools for data preprocessing, feature selection, model training, and evaluation, making it a versatile choice for customer churn prediction.
Pandas:
Pandas is a versatile data manipulation library in Python. It provides data structures and functions to efficiently handle and analyze structured data. Pandas is widely used for data preprocessing, feature engineering, and exploratory data analysis tasks in customer churn prediction projects.
NumPy:
NumPy is a fundamental library for numerical computations in Python. It provides support for multi-dimensional arrays, linear algebra operations, and mathematical functions. NumPy is often used in conjunction with other libraries for data manipulation and preprocessing tasks in customer churn prediction.
Matplotlib:
Finding trends in a dataset is made easier with the use of data visualisation. Python's Matplotlib library provides a complete tool for building static, animated, and interactive visualisations. Matplotlib makes difficult things possible and simple things easy.

ALGORITHMS

DECISION TREE:

A decision tree uses a tree structure to develop classification or regression models. It incrementally develops an associated decision tree while segmenting a data set into smaller and smaller parts. A decision node is represented by a leaf node, which has two or more branches and denotes a categorization or judgement. The root node is the topmost decision node in a tree and corresponds to the best predictor. Both category and numerical data can be processed using decision trees. Using a tree structure, decision trees construct classification or regression models. It employs a collection of if-then rules that are exhaustive and mutually exclusive for classification. Utilizing one training set of data at a time, the rules are successively learned. whenever a rule is learned, the tuples covered by the rules are removed

On the practise set, this procedure is continued until a termination requirement is satisfied. It is built using a top-down divide-and-conquer strategy. There should be categories for each attribute. If not, they should be discredited beforehand. The information gain concept is used to identify the attributes at the top of the tree since they have the greatest impact on classification. A decision tree may reflect anomalies brought on by noise or outliers and may be readily over-fitted, producing an excessive number of branches.

SUPPORT VECTOR MACHINE

In order to forecast and categorise data using machine learning, we use a variety of machine learning methods depending on the datasets or Support The vector machine is a linear model for classification and regression problems. It can resolve both linear and non-linear problems and is effective for a variety of real-world challenges. The basic idea behind SVM is that the algorithm creates a line or a hyper plane that separates the data into classes. I'll provide a high-level overview of SVMs in this blog article. I'll discuss the theory underlying SVMs, how they may be used to non-linearly separable datasets, and give a brief example of how SVMs are implemented in Python. I will delve more into the algorithm's mathematics in the next articles.

ARTIFICIAL NEURAL NETWORKS (ANN)

Neural networks (NNs) or neural nets are popular terms for computing architectures that are modeled after the biological neural networks that make up animal brains. An artificial neural network (ANN) is built on artificial neurons, which are a collection of interconnected units or nodes that roughly resemble the neurons in a biological brain. Each link can transmit a signal to nearby neurons, just like synapses do in the human brain.

After digesting signals provided to it, an artificial neuron can signal neurons that are connected to it. The "signal" at a connection is a real number, and the output of every neuron is determined by some non-linear function of the sum of its inputs. Connectors are referred to as edges. As learning occurs, the total weight of neurons and edges frequently changes. The weight changes the signal strength of the link by boosting or lowering it. It's possible for neurons to establish a threshold beyond which they won't send a signal.

RESULTS

'DF1'

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850	United Kingdom
...	...	...	...	...	...	...	...	...
319395	564852	82552	WASHROOM METAL SIGN	10	2011-08-30 17:23:00	1.45	14976	United Kingdom
319396	564852	21756	BATH BUILDING BLOCK WORD	3	2011-08-30 17:23:00	5.95	14976	United Kingdom
319397	564852	21908	CHOCOLATE THIS WAY METAL SIGN	7	2011-08-30 17:23:00	2.10	14976	United Kingdom
319398	564852	22116	METAL SIGN HIS DINNER IS SERVED	10	2011-08-30 17:23:00	0.79	14976	United Kingdom
319399	564852	23091	ZINC HERB GARDEN CONTAINER	2	2011-08-30 17:23:00	6.25	14976	United Kingdom

230474 rows × 8 columns

'DF2'

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
49034	540498	21485	RETROSPOT HEART HOT WATER BOTTLE	1	2011-01-09 10:06:00	4.95	17243	United Kingdom
49035	540498	22112	CHOCOLATE HOT WATER BOTTLE	1	2011-01-09 10:06:00	4.95	17243	United Kingdom
49036	540498	17091A	LAVENDER INCENSE IN TIN	6	2011-01-09 10:06:00	1.25	17243	United Kingdom
49037	540498	84813	SET OF 4 DIAMOND NAPKIN RINGS	6	2011-01-09 10:06:00	12.75	17243	United Kingdom
49038	540498	22795	SWEETHEART RECIPE BOOK STAND	3	2011-01-09 10:06:00	6.75	17243	United Kingdom
...	...	...	...	...	...	...	...	...
541904	581587	22613	PACK OF 20 SPACEBOY NAPKINS	12	2011-12-09 12:50:00	0.85	12680	France

Fig.3. The 2 data frames DF1 and DF2 representing the given ranges where the customers who purchased items from between 1st Dec 2010 to 31st Aug 2011 did make subsequent purchase in the period Sep 2011 to Dec 2011.

'ONLY CHURN'

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Churn
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850	United Kingdom	Churn
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850	United Kingdom	Churn
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850	United Kingdom	Churn
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850	United Kingdom	Churn
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850	United Kingdom	Churn
...	...	...	...	...	...	...	...	...	...
268027	C560372	M	Manual	-1	2011-07-18 12:26:00	4287.63	17448	United Kingdom	Churn
268431	C560420	M	Manual	-1	2011-07-18 15:11:00	1592.49	15369	United Kingdom	Churn
268476	C560430	M	Manual	-1	2011-07-18 15:21:00	611.86	13154	United Kingdom	Churn
270557	C560572	M	Manual	-1	2011-07-19 14:45:00	112.35	17065	United Kingdom	Churn
270559	C560574	M	Manual	-1	2011-07-19 14:56:00	106.40	14437	United Kingdom	Churn

3261 rows × 9 columns

Fig.4. Target variable creation for the customers who are only labelled as churn.

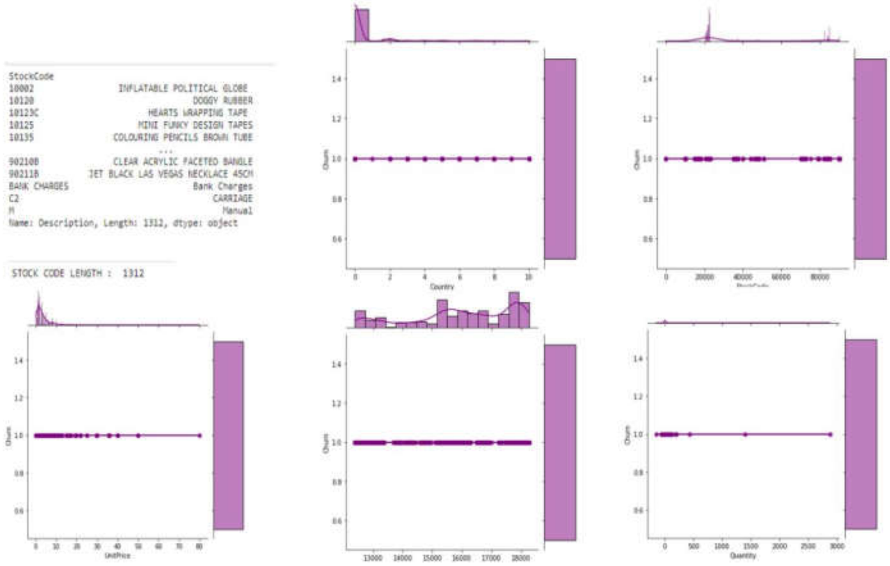

Fig.5. Customer churn prediction

Fig.6. Decision Tree using ID3 algorithm in dictionary format

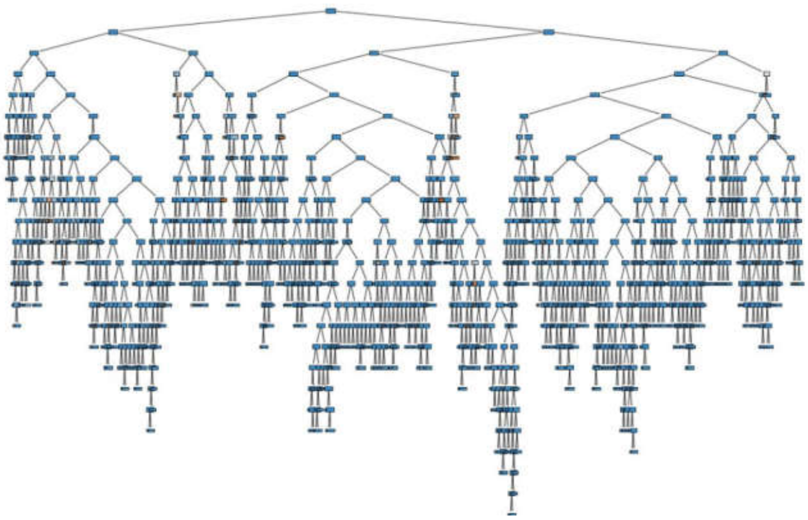

Fig.7. Plotting of the ID3 decision tree representing the complete classification

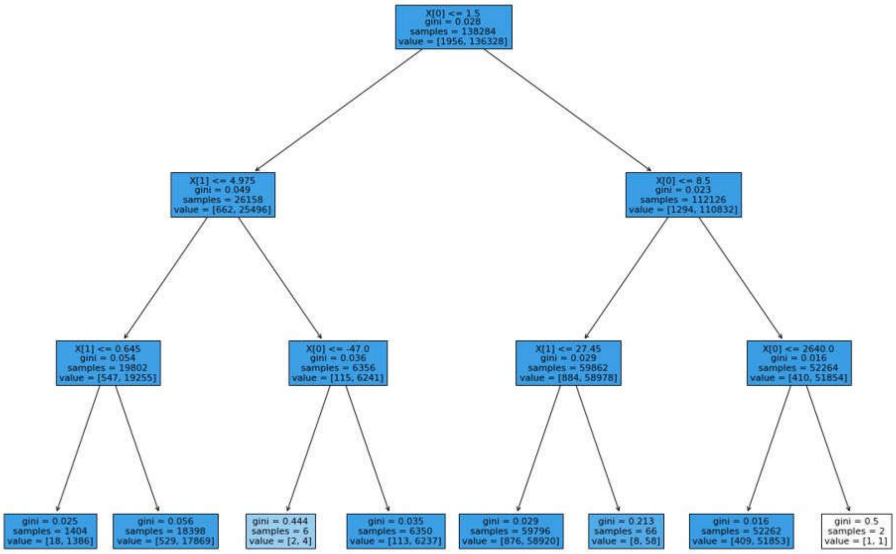

Fig.8. The plotting of the ID3 decision tree representing the complete classification for only 3 levels

```
# ACCURACY OF ID3 DT

y_pred = clf.predict(x_test)
print("Accuracy % :", metrics.accuracy_score(y_test, y_pred) * 100)
```

```
Accuracy % : 98.58900709835298
```

```
# CLASSIFICATION REPORT OF ID3 DT
print("CONFUSION MATRIX:\n", confusion_matrix(y_test, y_pred))
print("CLASSIFICATION REPORT:\n", classification_report(y_test, y_pred))
```

```
CONFUSION MATRIX:
 [[    0   808]
 [    5 56806]]
CLASSIFICATION REPORT:
               precision    recall  f1-score   support

       Churn       0.00      0.00      0.00       808
   Not Churn       0.99      1.00      0.99     56811

    accuracy                           0.99     57619
   macro avg       0.49      0.50      0.50     57619
weighted avg       0.97      0.99      0.98     57619
```

```
LINEAR SVM:

Accuracy % : 98.5924781756018
CONFUSION MATRIX:
 [[    0   808]
 [    3 56808]]
CLASSIFICATION REPORT:
               precision    recall  f1-score   support

       Churn       0.00      0.00      0.00       808
   Not Churn       0.99      1.00      0.99     56811

    accuracy                           0.99     57619
   macro avg       0.49      0.50      0.50     57619
weighted avg       0.97      0.99      0.98     57619

RBF SVM:

98.58900709835298
```

Fig.9. Accuracy and classification report of ID3 & SVM

ANN

```
#ANN
clf3 = MLPClassifier(max_iter = 5000, verbose = True)
clf3 = clf3.fit(x_train, y_train)
y_pred = clf3.predict(x_test)
```

```
Iteration 1, loss = 0.10282470
Iteration 2, loss = 0.07864294
Iteration 3, loss = 0.07822238
Iteration 4, loss = 0.07563560
Iteration 5, loss = 0.07753069
Iteration 6, loss = 0.07766999
Iteration 7, loss = 0.07754805
Iteration 8, loss = 0.07684078
Iteration 9, loss = 0.07653252
Iteration 10, loss = 0.07928821
Iteration 11, loss = 0.08099358
Iteration 12, loss = 0.07644377
Iteration 13, loss = 0.07542815
Iteration 14, loss = 0.07654819
Iteration 15, loss = 0.07917803
Iteration 16, loss = 0.08012774
Iteration 17, loss = 0.07643909
Iteration 18, loss = 0.07537057
Iteration 19, loss = 0.07474333
Iteration 20, loss = 0.07571476
Iteration 21, loss = 0.07682900
Iteration 22, loss = 0.07584297
Iteration 23, loss = 0.07749245
Iteration 24, loss = 0.07655167
Iteration 25, loss = 0.07740303
Iteration 26, loss = 0.07530750
Iteration 27, loss = 0.08223928
Iteration 28, loss = 0.07780841
Iteration 29, loss = 0.07488440
Iteration 30, loss = 0.07591913
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs. Stopping.
```

ACCURACY AND CLASSIFICATION REPORT OF ANN

```
# CLASSIFICATION REPORT OF ANN
print("Accuracy % :", metrics.accuracy_score(y_test, y_pred) * 100)
print("CONFUSION MATRIX:\n", confusion_matrix(y_test, y_pred))
print("CLASSIFICATION REPORT:\n", classification_report(y_test, y_pred))
```

```
Accuracy % : 98.59768479147583
CONFUSION MATRIX:
 [[    0   808]
 [    0 56811]]
CLASSIFICATION REPORT:
               precision    recall  f1-score   support

       Churn       0.00      0.00      0.00       808
   Not Churn       0.99      1.00      0.99     56811

    accuracy                           0.99     57619
   macro avg       0.49      0.50      0.50     57619
weighted avg       0.97      0.99      0.98     57619
```

Fig.10. Accuracy and classification report of ANN

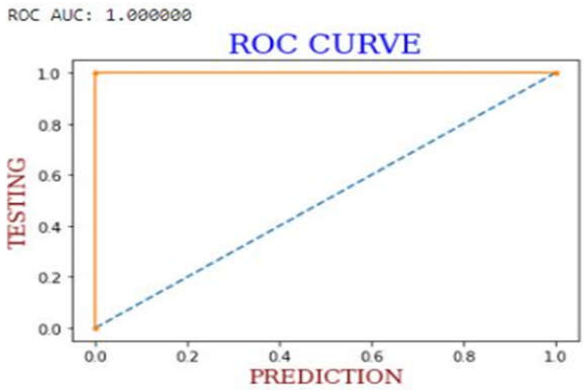

Fig.11. ROC Curve

CONCLUSION

In the analytical process, missing value analysis, exploratory analysis, model development, and model evaluation happened first. There will be a discovery of the test set with the highest accuracy score. This tool can assist in determining the Prediction of Bank Churn, which aids in providing customers with greater support.

Your business will be able to enhance customer retention rates, reduce retention expenses, and even safeguard future revenue from churning users with machine learning and deep analysis for customer churn prediction. By putting customer churn models into place at your company, you may keep more customers from leaving and increase revenue.

The customer churn prediction project has shown promising results in accurately identifying customers who are likely to churn. By utilizing advanced machine learning algorithms and analyzing relevant customer data, the project has provided valuable insights for businesses to take proactive measures in retaining their customers. The project has demonstrated the potential of predictive analytics in reducing customer churn rates and improving overall customer retention strategies.

The project involved several key steps, including data collection, data preprocessing, feature engineering, model selection, and evaluation. Various machine learning algorithms such as logistic regression, decision trees, random forests, and gradient boosting were employed to develop predictive models. The models were trained on historical customer data with churn labels and evaluated using appropriate performance metrics such as accuracy, precision, recall, and F1 score.

The results obtained from the project indicate that customer churn prediction is indeed feasible and effective. The predictive models achieved high accuracy and other favorable performance metrics, demonstrating their ability to accurately identify potential churners. This information can enable businesses to implement targeted retention strategies, such as personalized offers, loyalty programs, or proactive customer service, to reduce churn rates.

FUTURE SCOPE

Using real-time AI models to connect bank churn prediction. to efficiently carry out the work in a setting with artificial intelligence. Here, the project's goal is to integrate computer records with bank support in order to decrease customer turnover, increase bank safety, and improve bank customer assistance. This approach holds promise since data analysis and modeling methods, such as data mining, have the ability to create a knowledge-rich environment that can help to greatly raise the standard of Bank support.

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