International Journal of Research Publication and Reviews, Vol 4, no 11, pp 2776-2785 November 2023

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Improving Customer Retention with Churn Prediction Models

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ABSTRACT

In the competitive landscape of modern business, customer retention is a critical factor influencing the long-term success of enterprises. This research focuses on leveraging big data analytics to develop effective churn prediction models aimed at enhancing customer retention strategies. The study explores the vast potential of big data in capturing and analyzing customer-related information to identify patterns indicative of potential churn. By employing advanced machine learning algorithms and data-driven insights, the research aims to empower businesses with proactive measures to mitigate customer churn, ultimately fostering stronger and more enduring customer relationships. The findings and methodologies presented herein offer a comprehensive framework for businesses seeking to implement data-driven approaches for customer retention in the era of big data analytics.

Keywords : Big Data Analytics; Churn Prediction; Customer Churn; Machine Learning; Targeted Customer Retention

1. Introduction

In the rapidly evolving landscape of modern business, customer retention has become a critical factor for sustained success. The introduction of big data analytics has transformed how organizations methodology customer relationship administration, enabling them to delve into vast datasets to extract meaningful insights. This paper explores the use of big data analytics and churn prediction models as a proactive strategy to enhance customer retention.

1.1. Background

In today's hypercompetitive markets, acquiring new customers is a formidable challenge, often requiring significant resources. However, the real measure of a company's success lies in its ability to retain existing customers. Customer churn, the phenomenon where customers discontinue their association with a company, poses a substantial threat to long-term profitability and growth. Identifying and addressing the factors contributing to churn has thus become a strategic imperative for businesses.

1.2. Significance of Customer Retention

Customer retention is not merely about maintaining a customer base; it directly impacts a company's bottom line. Retained customers tend to be more profitable over time, as the cost of retaining an existing customer is typically lower than acquiring a new one. Moreover, satisfied and loyal customers often become brand advocates, contributing to positive word-of-mouth and attracting new business.

1.3. The Role of Big Data Analytics

The proliferation of digital interactions and transactions has resulted in an unprecedented volume of data. Big data analytics, with its advanced processing capabilities, allows organizations to sift through this vast sea of information to uncover patterns, trends, and insights. Applying analytics to customer data provides a nuanced understanding of behavior, preferences, and potential indicators of churn.

1.4. Churn Prediction Models

Churn prediction models leverage big data analytics to identify customers who are at risk of churning. By analyzing historical data, these models can discern patterns and behaviors that precede customer attrition. Machine learning algorithms, such as decision trees, logistic regression, and neural networks, can be trained on large datasets to predict the likelihood of churn for individual customers.

1.5. Objectives of the Paper

1) Explore the importance of customer retention in contemporary business environments.
2) Highlight the advantages of utilizing big data analytics in understanding customer behavior.
3) Investigate the role of churn prediction models in proactively identifying and addressing customer churn.
4) Showcase real-world examples and case studies of organizations that have successfully implemented churn prediction models to improve customer retention.

2. Literature Review

The literature underscores the evolution of churn prediction models from traditional statistical approaches to advanced machine learning techniques. Furthermore, the nuanced exploration of factors contributing to churn provides valuable insights for the development of more accurate and actionable models. Future research directions may focus on the integration of real-time data, explain ability of model predictions, and industry specific nuances in churn dynamics.

2.1 Churn Prediction Models

Customer churn, the phenomenon of customers discontinuing their association with a service or product, is a critical challenge for businesses across various industries. Churn prediction models have emerged as indispensable tools for organizations seeking to proactively address customer attrition. The literature reflects a growing interest in developing and enhancing these models using a variety of methodologies.

2.1.1 Traditional Statistical Models

Early research in churn prediction predominantly utilized statistical models such as logistic regression and decision trees. These models often relied on historical customer data, including transaction frequency, customer demographics, and usage patterns. While effective to some extent, these models faced limitations in handling the complexity of dynamic customer behaviors and evolving market conditions.

2.1.2 Machine Learning Approaches

Recent studies highlight a paradigm shift towards machine learning (ML) approaches for churn prediction. Support Vector Machines (SVM), Random Forests, and Gradient Boosting Machines have gained popularity due to their ability to capture intricate patterns in large datasets. Additionally, neural networks, particularly recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), are increasingly explored for their capacity to model sequential dependencies in customer interactions over time.

2.1.3 Ensemble Models

Ensemble models, combining predictions from multiple base models, have emerged as a powerful strategy to enhance the robustness of churn prediction. Bagging and boosting techniques, such as Random Forests and AdaBoost, have demonstrated improved accuracy by leveraging diverse model perspectives and mitigating individual model weaknesses.

2.2 Factors Contributing to Churn

Understanding the factors influencing customer churn is fundamental to the development of accurate prediction models. The literature reveals a multifaceted landscape of contributors, encompassing both internal and external elements.

2.2.1 Customer Satisfaction and Experience

Several studies emphasize the pivotal role of customer satisfaction and experience in predicting churn. Dissatisfaction with service quality, unmet expectations, and poor customer service have been identified as significant precursors to customer attrition. Analyzing sentiment from customer feedback and social media interactions has emerged as a novel approach to gauge satisfaction levels.

2.2.2 Pricing and Contractual Factors

Price sensitivity and contract terms play a crucial role in customer decisions to stay or leave. Research suggests that sudden price hikes, hidden fees, and unfavorable contract conditions contribute significantly to churn. Churn prediction models must incorporate pricing dynamics and contract analysis for a comprehensive understanding of customer behavior.

2.2.3 Usage Patterns and Engagement Metrics

Customer engagement metrics, including frequency of product use, session durations, and feature adoption rates, offer valuable insights into customer loyalty. Studies highlight the importance of monitoring user behavior to detect early signs of disengagement and predict potential churn. Machine learning models excel in capturing intricate patterns within these usage metrics.

2.2.4 Socio-Demographic Variables

Demographic factors, such as age, income, and geographic location, continue to be explored as potential indicators of churn. While these variables may not solely determine customer behavior, they contribute to segmentation strategies that enhance the precision of churn prediction models.

3. Methodology

We designed a predictor by choosing a model class (Naïve Bayes classification, decision tree) in Microsoft Azure Workbench environment. The predictor in a local environment was tested with varied arguments ranging from 0.01 to 10 for every argument, a new job was executed, and the result produced showed the difference in accuracy rates. In our proposed work, we focused only on voluntary churn and not on involuntary churn. In voluntary churn, the customer decides to culminate his services with the service provider. Whereas in an involuntary churn, the service provider culminates its association with the customer due to bill arrears

3.1. Targeted positive Customer retention

While many mobile operators employ proactive retention strategies to curb subscriber churn, their success in doing so has been limited. Mobile number portability allows subscribers to switch operators swiftly, contributing to the persistent rise in churn globally. Operators commonly offer incentives such as year-long contracts or free minutes for several months to retain subscribers and mitigate churn. These incentives prove somewhat effective for post-paid subscribers but fall short for the majority of prepaid subscribers, who constitute 90% of the market.

Addressing churn proactively before subscriber's port out is crucial. Establishing proactive retention strategies involves the following steps:

1. Define Churn Models: Develop churn models tailored for both prepaid and post-paid subscribers to form the foundation of proactive retention practices.

2. Build Predictive Churn Models: Construct predictive churn models as tools to identify subscribers at risk of churn, enabling the telecom company to take preventive measures.

3. Design Targeted Offers: Based on predictive churn model results, create customized offers for various subscriber groups predicted to churn. Offers may include free monthly minutes for a specified duration or discounts on fixed post-paid plans for loyal subscribers.

4. Pilot Phase: Implement a pilot phase to assess the effectiveness of materials and agents involved in retention efforts for churners. This phase involves examining the outcomes and refining strategies accordingly.

Retaining existing subscribers poses an increasingly challenging task, emphasizing the need for robust proactive retention measures in the telecommunications industry.

3.2. Four step implementations

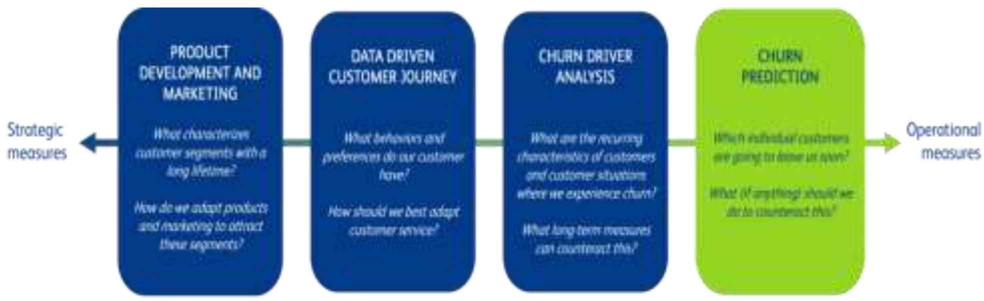

Figure 1: Four-Step Implementations.

1) Data Preparation Phase:

During the data preparation phase in the proposed work, once the prerequisites are met, implementation commences by initiating a new project in the Azure Machine Learning Workbench environment. Subsequently, a distinct data preparation package is created for the telecommunications industry dataset. Azure Workbench offers built-in packages such as Python, Spark, scikit-learn, and Matplotlib to facilitate the execution of scripts seamlessly. In this instance, Python/PySpark code is generated to invoke the data preparation package.

2) Model Creation Phase:

The model creation phase is a pivotal stage in the proposed work, where the prediction model takes shape. Following the initial data preparation phase, the Azure environment and dataset are ready for the application of machine learning. Python is used to code the model creation. Azure provides various environments for script execution, namely the Local environment, Local Docker environment, and Local Azure CLI window. Our project specifically executes in the local environment. Running scripts in the Local Docker environment requires the installation and activation of the Docker engine locally on the system. Similarly, to execute scripts against the Local Azure CLI window, either a remote Azure VM or an Azure HD Insight Spark cluster must be created.

3) Model Deployment Phase:

After the model creation, the relevant model file, in this case, the "pickle" file, is located. The pickle module in Python is a crucial algorithm for serializing and de-serializing a Python object structure. Following the selection of the appropriate model file, a scoring script and a schema file are generated. Before initiating web service creation, the environment is prepared, and a real-time web service is created and executed. The results of the web service are examined in Azure blob storage as blob data.

4) Advanced Data Preparation Phase:

In the advanced data preparation phase, the data is initially prepared using the ML data preparation tool. The prepared data is then imported and transformed to generate a test dataset. Once the data is prepared, a data package for preparation is created and executed. Decision trees represent classification and regression models in a tree structure. The dataset is iteratively fragmented into smaller subsets, culminating in the creation of a decision tree. The Naive Bayes algorithm is a widely preferred classification algorithm, derived from the Bayesian theorem of classification. It is particularly well-suited for problems involving high-dimensional inputs.

Parameter estimation for naive Bayes models employs the method of maximum likelihood. Despite its oversimplified assumptions, it often outperforms in many complex real-world situations. An advantage is its requirement for a small amount of training data to estimate parameters using Python. For multiple input files, a training set of data is generated by reusing the data preparation package. Finally, the scripts are executed in the local Azure CLI window and Cloud Azure HD Insight environment.

4. Algorithm

4.1. Naïve Bayes Classification Algorithm

The Naive Bayes algorithm stands out as a highly favored and widely used classification algorithm, originating from the Bayesian theorem of classification. Its optimal performance is observed in scenarios with high-dimensional inputs. Parameter estimation for Naive Bayes models relies on the method of maximum likelihood. Despite its simplifying assumptions, the algorithm frequently outperforms in various complex real-world situations.

4.2. Bayes Theorem

Equation (1): $P(c|x) = \frac{P(x|c) \cdot P(c)}{P(x)}$

Definition 4.2.1: $P(c|x)$ denotes the posterior probability of class c (target) given predictor x (attributes).

Equation (2): $P(x)$

Definition 4.2.2: $P(c)$ denotes the prior probability of class.

Equation (3): $P(c|x) = P(x_1|c) \times P(x_2|c) \times \ldots \times P(x_n|c)$

Definition 4.2.3: $P(x|c)$ denotes the likelihood.

Equation (4): $P(c|X) = P(x_i|c)$

Definition 4.2.4: $P(x)$ - prior probability of predictor.

4.3. Applications of Naive Bayes Classification

1) The Naive Bayes algorithm is applied in classifying textual content.
2) It is commonly used for spam filtering in emails.
3) A hybrid Recommender System can be developed using the Naive Bayes Classifier and Collaborative Filtering.

4) It is a preferred algorithm for designing online applications.

4.4. Decision Tree Algorithm

The decision tree represents classification and regression models in a tree structure. The dataset is divided into smaller subsets at each iteration, leading to the creation of a decision tree. The result is a decision tree comprising decision nodes and leaf nodes. Decision nodes have more than two sub-branches, and leaf nodes signify a classification or decision. The top node, known as the root node, represents the best predictor. Decision trees can handle both categorical and numerical data.

5. Experimental Result Investigation/Analysis

The entire experiment is conducted on the Azure Workbench (Preview) version with Docker explicitly installed. Azure Workbench is compatible only with Windows 10 and 10 Pro, requiring a Microsoft and Azure account. The four implementation stages are detailed in the methodology section. The dataset choice is flexible, with Azure accommodating sizes from small to very large. All necessary Python packages are pre-installed in the workbench. The proposed work can be executed in the one-month free trial version, but advanced features may necessitate a paid version. Hardware and software specifications for the experimentation system are outlined in the following section.

6. System Requirements Specifications

The experiments were carried out on a 64-bit Windows 10 system. The experiments are compatible with both Mac OS and Windows 10 or Windows 10 Pro. For software requirements, a Microsoft account (mandatory) with either a free or paid Microsoft Azure account is necessary for deploying services on the cloud. A Community version of Docker is also required for operating-system-level virtualization, commonly known as containerization. To facilitate a quick launch of Docker, the Docker Toolbox can be installed, comprising the Docker Quick Start Terminal, Oracle VM VirtualBox, and Kinematic.

6.1. Microsoft Azure

The Microsoft Azure Machine Learning service offers an integrated, end-to-end analytical solution, supporting data scientists in data preparation, experimental development, and model deployment at a cloud scale. Machine Learning, a data science technique enabling computers to forecast future behavior, outcomes, and trends without explicit programming, has become a transformative force in technology. Examples include ML-driven product recommendations during online shopping, fraud detection during credit card transactions, and the autonomous navigation of robot vacuum cleaners.

6.2. Machine Learning in Microsoft Azure Cloud

Azure ML is a cloud-enabled predictive analytic service that simplifies model creation and deployment for predictive analytics. Azure Machine Learning provides both tools and built-in packages for model predictive analytics, along with fully managed services to convert predictive models into functional web services.

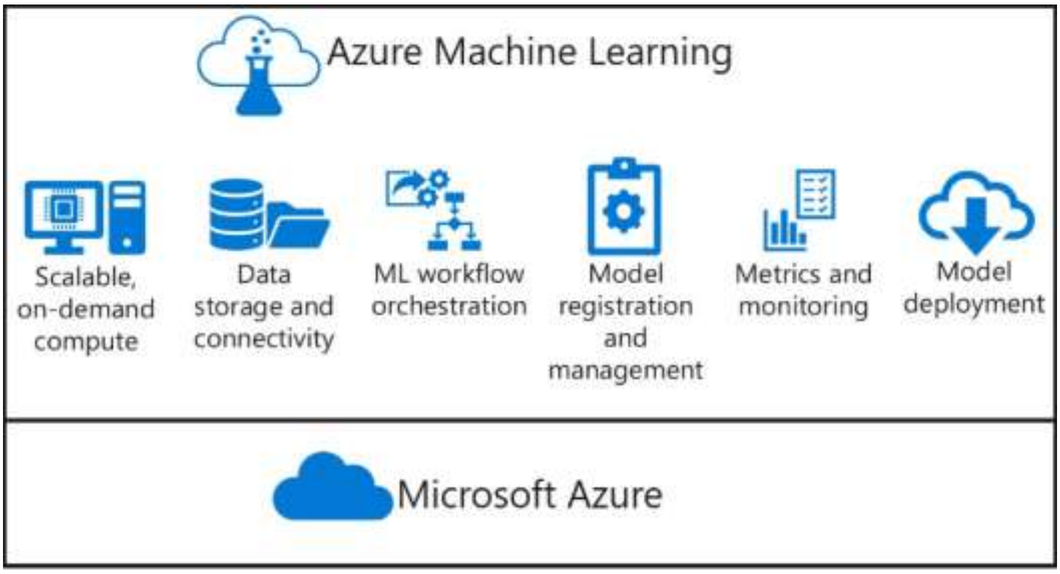

Figure 2 : Azure Machine Learning Service

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
1	age	annualinc	calldropra	callfailure	callingnur	customeri	customer	education	gender	homeowr	maritalsta	monthlyb	noadditio	numberof	numberof	numdays	occupatio	penaltyto	state	totalmins	unpai
2	12	168147	0.06	0	4.25E+09	1	Yes	Bachelor (	Male	Yes	Single	71	\N	0	7	96	Technolo	371	WA	15	
3	12	168147	0.06	0	4.25E+09	1	Yes	Bachelor (	Male	Yes	Single	71	\N	0	7	96	Technolo	371	WA	15	
4	42	29047	0.05	0.01	4.25E+09	2	Yes	Bachelor (	Female	Yes	Single	8	\N	1	4	14	Technolo	43	WI	212	
5	42	29047	0.05	0.01	4.25E+09	2	Yes	Bachelor (	Female	Yes	Single	8	\N	1	4	14	Technolo	43	WI	212	
6	58	27076	0.07	0.02	4.25E+09	3	Yes	Master or	Female	Yes	Single	16	\N	0	2	55	Technolo	403	KS	216	
7	58	27076	0.07	0.02	4.25E+09	3	Yes	Master or	Female	Yes	Single	16	\N	0	2	55	Technolo	403	KS	216	
8	20	137977	0.05	0.03	4.25E+09	4	Yes	PhD or eq	Male	No	Single	74	\N	1	7	73	Technolo	76	KY	412	
9	20	137977	0.05	0.03	4.25E+09	4	Yes	PhD or eq	Male	No	Single	74	\N	1	7	73	Technolo	76	KY	412	
10	36	136006	0.07	0	4.25E+09	5	Yes	High Scho	Male	Yes	Married	81	\N	0	5	14	Technolo	436	ND	416	
11	36	136006	0.07	0	4.25E+09	5	Yes	High Scho	Male	Yes	Married	81	\N	0	5	14	Technolo	436	ND	416	
12	67	246906	0.05	0.01	4.25E+09	6	Yes	High Scho	Female	Yes	Married	19	\N	1	2	32	Technolo	108	OK	113	
13	67	246906	0.05	0.01	4.25E+09	6	Yes	High Scho	Female	Yes	Married	19	\N	1	2	32	Technolo	108	OK	113	
14	14	244935	0.07	0.02	4.25E+09	7	Yes	High Scho	Male	Yes	Single	27	\N	3	0	73	Technolo	468	AZ	116	
15	14	244935	0.07	0.02	4.25E+09	7	Yes	High Scho	Male	Yes	Single	27	\N	3	0	73	Technolo	468	AZ	116	

Figure 3 : Dataset

6.3. Azure Machine Learning Workbench

Azure Machine Learning Workbench is a client application functioning as either a desktop application or command-line tool for Windows and MacOS. It manages machine learning solutions throughout the data science life cycle, which includes three predominant phases:

1) Data Ingestion and Preparation
2) Model Development and Experiment Management
3) Model Deployment in Multi-Targeted Environments

Core functionalities of Azure Machine Learning Workbench include:

1) Facilitating data preparation, simplifying the logic of learning data transformation with relevant examples.
2) Providing various built-in services such as client UX, Jupyter Notebook, etc.
3) Monitoring experiments through an overall run history.
4) Offering inbuilt Python and Spark packages to aid data source abstraction.
5) Autosaving option for convenience.

6.4. Characteristics of Input Data

The primary cause of churn is customer dissatisfaction, which eventually transforms into disloyalty towards the service provider. Dissatisfaction may stem from various reasons such as compromised service quality, high costs, or time delays. The sources of customer discontent vary over time and interests. The input data in our proposed work is categorized for better comprehension as follows: Demographic Data, Usage Level Data, Quality of Service Data, and Other Features/Marketing Data.

1**. Demographic Data**: Data related to the population and geography of a region.

2. **Usage Level Data:** Details of customer call history, including call duration, caller location, call count, call limit, etc.

3. **Quality of Service (QoS) Data:** Primarily concerned with the call experience, covering aspects like quality, network coverage, connection interruption, voice clarity, etc.

4. **Other Feature/Marketing Data:** Encompasses data related to promotions, such as SMS, emails, advertisements, new competition, call tariffs, etc.

6.5. Dataset

The dataset utilized in our proposed work is a substantial sample customer dataset comprising 20,469 records and 26 attributes. It includes basic customer information like Annual Income, Call Drop Rate, Call Fault Rate, Calling Number, Customer ID, Customer Usage, Education, Gender, Home Owner, Marital Status, Monthly Billed Amount, Number of Additional Lines, Number of Complaints, Expiration Period, Occupation, Penalty To Switch, State, Total Minutes Used in Last Month, Unpaid Balance, User Internet Service, User Voice Service, Percentage Call Outside Network, Total Call Duration, Average Call Duration, Churn, Year, and Month. The pivotal attribute in the dataset is churn, and the data was recorded over a period of two months in the year 2015.

6.6. Training and Testing in Azure Environment

The training and testing procedure in Azure is executed by Analysis Services, which randomly samples input data, maintaining similarity between testing and training sets to minimize data discrepancies' effects. Azure simplifies training and testing using the Data Mining Wizard, defaulting to dividing the dataset into training and testing data. The model training employs churn records, while testing involves non-churn records. The standard 70:30 ratio can be adjusted to match specific requirements using Analysis Services. Following the model creation phase, the training dataset processes the model, and testing is conducted by predicting against the test data, containing all possible prediction values for the attribute.

6.7. Performance Metrics

Various metrics are available to assess prediction algorithm performance, including entropy, purity, true positive and negative rates, accuracy, precision, F-Measure, and computation time. For evaluation purposes, precision, recall, F-Measure, accuracy, sensitivity, specificity, training period, and prediction time are used. Customer success and support metrics play a crucial role in evaluating progress, including expansion revenue, customer satisfaction, and loyalty prediction.

7. Result Screenshots

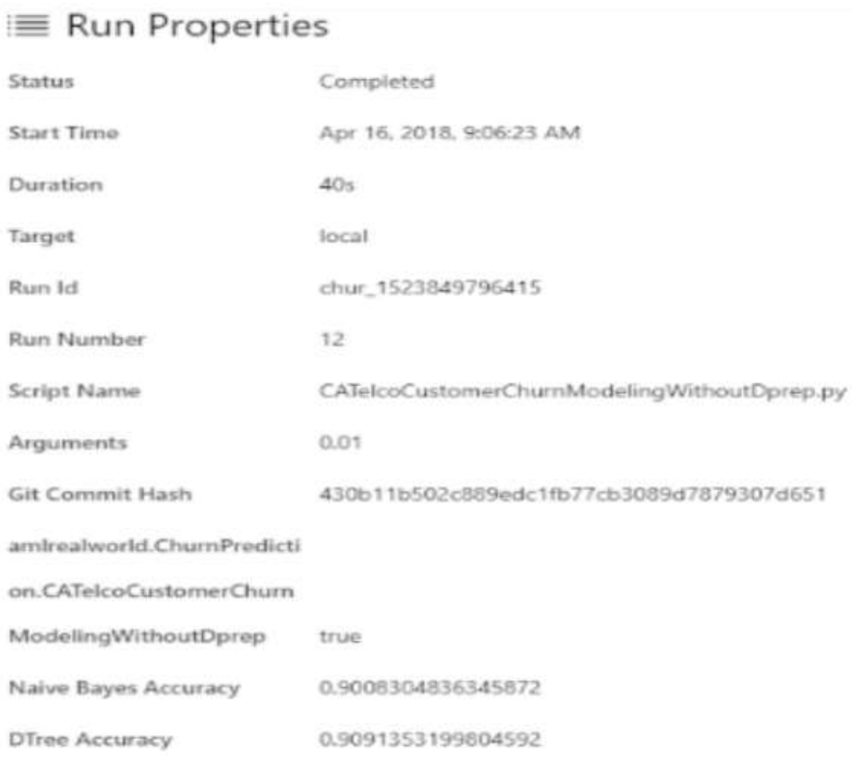

Figure 5: Accuracy Comparison between Naïve Bayes and Decision Tree Algorithms.

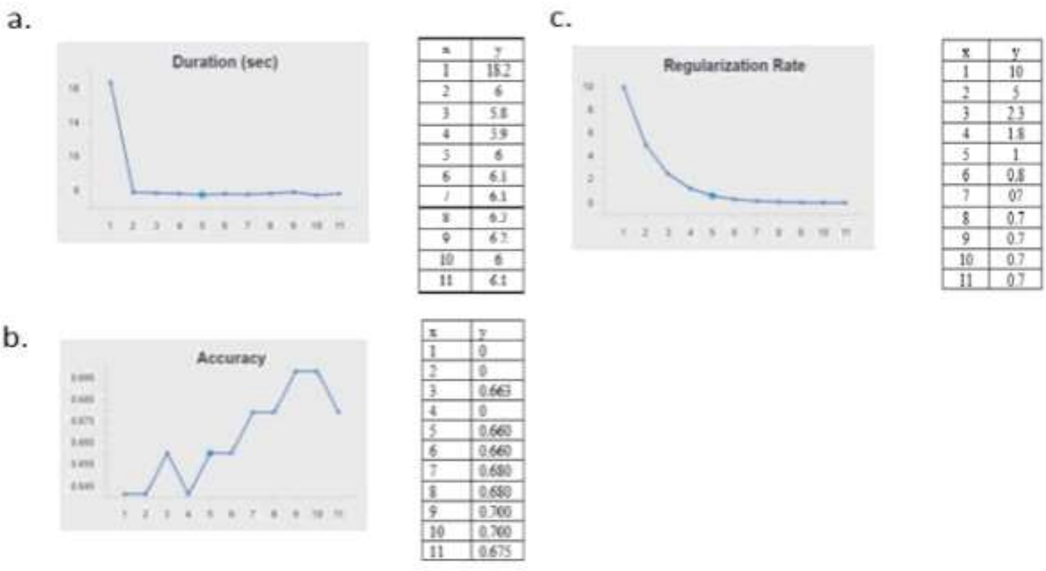

Figure 6: a. Duration Graph Displaying Job Execution Time.

b. Accuracy Graph Illustrating Accuracy Across Multiple Job Executions.

c. Regulation Graph Reflecting Changes in Regulation Rate Over Time.

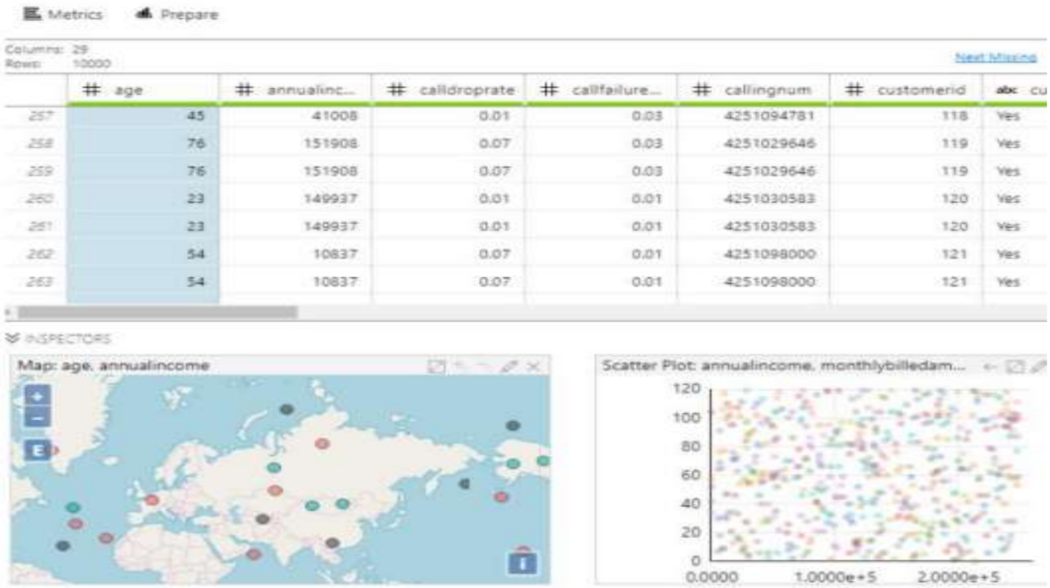

Fig. 7: Metrics Representation of the Dataset.

8. Result Analysis

8.1. Churn Prediction

For each predictor, the probability of churners is estimated by combining information from three output graphs: Accuracy, Regulation rate, and Duration. A steeper graph indicates higher accuracy. Various sets of graphs are generated for different input regulation rates. The primary goal is to determine whether a customer is likely to churn, achieved by identifying a threshold value from continuous probabilistic outputs. Results, indicating churn and no churn, are typically visualized using a lift curve. The lift curve, presented as a multi-class ROC, contrasts churners and non-churners to ascertain the probability of churners.

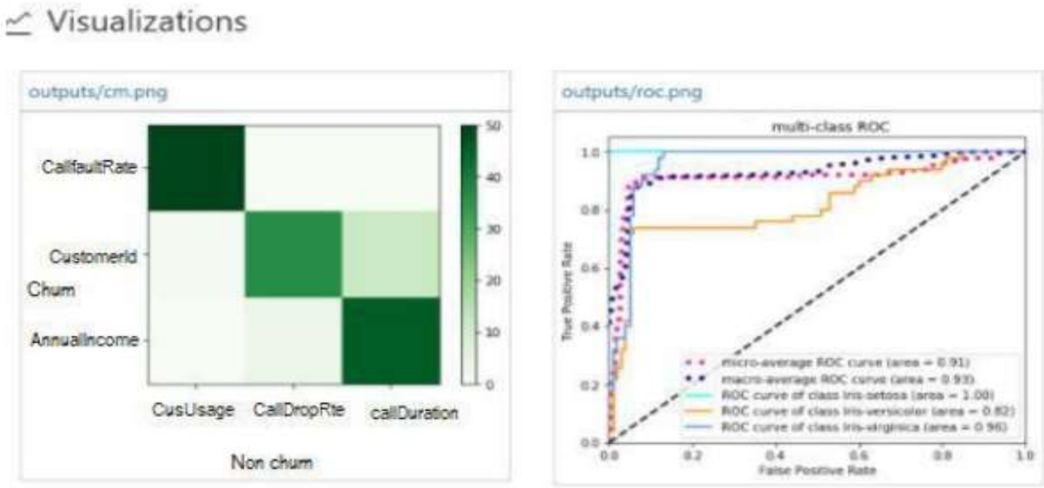

Fig. 8: Multi-Class ROC Graph.

9. Conclusion

Predicting churn and implementing effective retention strategies are crucial for industries in intense competition. A robust retention strategy, combined with an optimal churn prediction model, is essential in today's competitive landscape. The study explores two machine learning classification algorithms for churn prediction: Naïve Bayes Classification and Decision Tree. Leveraging machine learning with big data analytics tools creates an environment conducive to accurate churn prediction. Businesses are expected to prioritize churn prediction with retention strategies as a preventive measure.

9.1. Ongoing Research

The research will progress until the most optimal churn model is formulated, aiming for the targeted accuracy. Future stages will expand in diverse directions, testing the model with different datasets and exploring alternative machine learning algorithms for enhanced efficiency. Different customer retention techniques will be explored to refine output accuracy. Churn prediction remains a multifaceted concept, largely unexplored in various dimensions. The perpetual need for an improved churn prediction model is fundamental, especially in the telecommunications industry. The scope for future research in this field remains boundless.

References

[1] Keramati A., Jafari-Marandi R., Aliannejadi M., Ahmadian I., Mozaffari M., Abbasi U. (2014), "Improved churn prediction in telecommunication industry using data mining techniques",Applied Soft Computing Journal, 24 , pp. 994-1012.

[2] Michael C. Mozer, Richard Wolniewicz, David B. Grimes, Eric Johnson, and Howard Kaushansky," Predicting subscriber dissatisfaction and improving retention in the wireless telecommunications industry". IEEE Transactions on Neural Networks, 11:690–696, 2000.

[3] Adnan Amin, Sajid Anwar, Awais Adnan, Muhammad Nawaz, Khalid Alawfi, Amir Hussain and Kaizhu Huang, "Customer Churn Prediction in Telecommunication Sector using Rough Set Approach",Neurocomputing,http://dx.doi.org/10.1016/j.neucom.2016.12.009

[4] Etaiwi, W., Biltawi, M., Naymat, G,"Evaluation of classification algorithms for banking customer's behavior under apache spark data processing system" Procedia Comput. Sci. 113, 559–564 (2017)

[5] A. A. Ahmed, and D. Maheswari, "Churn prediction on huge telecom data using hybrid firefly-based classification," Egyptian Informatics Journal, 2017.

[6] Harnie, D., Vapirev, A.E., Wegner, J.K., Gedich, A., Steijaert, M., Wuyts, R., & De Meuter, W. (2015)," Scaling machine learning for target prediction in drug discovery using apache spark" In Proceedings of the 15th IEEE/ACM International Symposium on Cluster Cloud and Grid Computing.

[7] Junxiang Lu, "Predicting Customer Churn in the Telecommunications".

[8] Keramati A, Jafari-Marandi R, Aliannejadi M, Ahmadian I, Mozzafari M, Abbasi U (2014), "Improved churn prediction in telecommunication industry using data mining techniques", Appl Soft Comput 24:994–1012.

[9] Xie Y, Li X, Ngai EWT, Ying W (2009), "Customer churn prediction using improved balanced random forests" Expert Syst Appl 36(3):5445–5449

[10] Au, W., Chan, C., & Yao, X (2003), "A novel evolutionary data mining algorithm with applications to churn prediction", IEEE Transactions on Evolutionary Computation, 7, 532–545. https://doi.org/10.1109/TEVC.2003.819264.

[11] Boser, B., Guyon, I., & Vapnik V (1992), "A training algorithm for optimal margin classifiers", In Proceedings the fifth annual ACM workshop on computational learning theory, (pp. 144–152).

[12] Pittsburgh, PA: ACM Press. Bradley, A. P (1997), "The use of the area under the roc curve in the evaluation of machine learning algorithms", Pattern Recognition, 30, 1145–1159. https://doi.org/10.1016/S0031-3203(96)00142-2.

[13] Burges, C. J. C (1998), "A tutorial on support vector machines for pattern recognition", Data Mining and Knowledge Discovery, 2(2),121–167. https://doi.org/10.1023/A:1009715923555.

[14] Coussement, K., & den Poe, D. V (2008), "Churn prediction in subscription services: An application of support vector machines while comparing two parameter selection techniques", Expert Systems with Applications, 34, 313–327. https://doi.org/10.1016/j.eswa.2006.09.038.

[15] Domingos, P., & Pazzani, M. J (1997), "On the optimality of the simple bayesian classifier under zero-one loss", Machine Learning, 29(2–3), 103–130. https://doi.org/10.1023/A:1007413511361.

[16] Hadden, J., Tiwari, A., Roy, R., & Ruta, D (2006), "Churn prediction: Does technology matter", International Journal of Intelligent Technology, 1(2).

[17] Henley(2009)., Hosmer, D., & Lemeshow, S (1989), "Applied logistic regression" , New York: Wiley.

[18] Huang, B., Kechadi, M.-T., & Buckley, B (2010), "A new feature set with new window techniques for customer churn prediction in landline telecommunication", Expert Systems with Applications, 37(5), 3657–3665. https://doi.org/10.1016/j.eswa.2009.10.025.

[19] Hung, S.-Y., Yen, D. C., & Wang, H.-Y (2006), "Applying data mining to telecom churn management", Expert Systems with Applications, 31, 515–524. https://doi.org/10.1016/j.eswa.2005.09.080.

[20] Japkowicz, N (2000), "Learning from imbalanced data sets: A comparison of various strategies", (pp. 10–15).

[21] AAAI Press. Japkowicz, N (2006), "Why question machine learning evaluation methods", In AAAI Workshop.

[22] Boston. John, H., Ashutosh, T., Rajkumar, R., Dymitr, R. (2007) "Computer assisted customer churn management: State-of-the-art and future trends"

[23] Jolliffe, I. T (1986), "Principal component analysis",New York: Springer https://doi.org/10.1007/978-1-4757-1904-8.

[24] L. Xi, Y. Wenjing, L. An, N. Haiying, H. Lixian, Q. Luo, and C. Yan, "Churn Analysis of Online Social Network Users Using Data Mining Techniques", Preced. Int. multi Conf. Eng. Comput. Sci., no. 1, pp. 14–16, 2012.

[25] W. Verbeke, D. Martens, and B. Baesens, "Social network analysis for customer churn prediction",Appl. Soft Comput., vol. 14, pp. 431– 446, Jan. 2014. https://doi.org/10.1016/j.asoc.2013.09.017.

[26] D. Archambault, N. Hurley, and C. T. Tu (2013), "ChurnVis: Visualizing mobile telecommunications churn on a social network with attributes," Adv. Soc. Networks Anal. Min (ASONAM), 2013 IEEE/ACM, pp. 894–901. https://doi.org/10.1145/2492517.2500274.

[27] K. Dasgupta, R. Singh, B. Viswanathan, D. Chakraborty, S. Mukherjea, A. A. Nanavati, and A. Joshi (2008), "Social ties and their relevance to churn in mobile telecom networks", in Proceedings of the 11th international conference on Extending database technology Advances in database technology - EDBT '08, pp. 668–677. https://doi.org/10.1145/1353343.1353424.

[28] J. David Nunez-Gonzalez, M. Grana, and B. Apolloni (2014), "Reputation features for trust prediction in social networks", Neurocomputing, vol. 166, pp. 1–7. https://doi.org/10.1016/j.neucom.2014.10.099.

[29] U. Prasad Devi and S. Madhavi (2012), "Prediction Of Churn Behavior Of Bank Customers", Bus. Intell. J., vol. 5, no. 1, pp. 96– 10.

[30] K. Chitra and B. Subashini (2011), "Customer Retention in Banking Sector using Predictive Data Mining Technique", ICIT 2011 5th Int. Conf. Inf. Technol.