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Customer Behavior Analysis for Forecasting Customer Attrition: An Artificial Intelligence Approach

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***Abstract*— In the telecom sector, the phases of acquisition, build-up, peak, decline, and attrition are commonly included in the customer's lifetime. Nevertheless, telecom businesses often struggle to analyze the vast amounts of client data they generate, which hinders their ability to forecast customer attrition accurately and leads to revenue loss. To help customer retention managers anticipate customer attrition and develop effective retention strategies, this research aims to design a predictive model that supports their efforts. As an empirical and iterative process, Artificial Intelligence (AI) and Machine Learning (ML) were used to train several models and enhance the accuracy of churn prediction. Many technologies used today, such as artificial intelligence (AI), machine learning (ML), and data mining, were developed during the digital era. To conduct various research studies to predict customer churn, mobile operators can utilize "Big Data" from customer records, a defining feature of the telecom industry. Based on each user's distinct attributes, the model interface predicts the likelihood of churn and supports various tasks. This research provides a framework for creating successful retention strategies and sheds light on the variables that cause customers to leave the telecom industry. The study's findings encourage telecom firms to become more competitive and promote long-term growth by strengthening customer strategy and improving predictive performance. Using the Tel-data dataset, the study successfully applied AI and ML techniques, such as logistic regression, to create a prediction model that could reliably identify consumers at risk of leaving. This enables businesses to conduct targeted retention campaigns, thereby enhancing client loyalty and satisfaction.**

***Keywords*— Predictive analytics; customer churn prediction; predictive modeling; machine learning.**

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I. INTRODUCTION

The telecommunications sector has been expanding rapidly in recent years, driven by a shift in lifestyle toward the ever-present internet and technological advancements. Telecommunications networks are integrating Machine Learning (ML) along with an Artificial Intelligence (AI) approach to increase security, optimize network performance and customize user experiences [1], [2]. Predictive maintenance, network optimization, and intelligent customer service solutions are made possible by these technologies, which eventually improve performance and satisfy customers [3]. Because telecommunications companies are highly competitive, predicting and managing churn is one of their biggest challenges. Nonetheless, a range of machine learning strategies is employed to support a mobile company's client retention efforts. Based on their individual goals, specific data mining applications, such as fraud detection, image processing, and speech recognition, are well-suited to specific machine learning techniques. This makes it clear that machine learning is essential to data mining, a process that is also crucial to the field of data science. Many of the technologies used today, such as AI, ML, and data mining, were developed during the digital era [4]. To conduct various research studies to predict customer churn, mobile operators can utilize "Big Data" from customer records, a defining feature of the telecom industry. To find patterns in data, these researchers can employ machine learning techniques, including neural network algorithms (Multi-Layer Perceptron), K-Nearest Neighbor, decision trees, random forest, and Logistic Regression, which are algorithms of statistical machine learning.

These patterns aid data classification, prediction-making, and, ultimately, the creation of an appropriate model based on that particular set of data. Based on observations, the stages of acquisition, attrition, build-up, decline, and peak are often included in the customer life cycle. The challenge of analyzing the patterns and behaviors visible in the enormous amounts of big data created by customers is one of the biggest obstacles facing telecom firms. As a result, it becomes difficult to accurately estimate client attrition, which may lead to these businesses incurring financial losses.

In this study, Logistic Regression (LR) is employed as a crucial statistical tool to predict and classify customer churn behavior. Unlike traditional regression methods, Logistic Regression is proficient in handling binary outcomes, rendering it particularly apt for the analysis of telecom customer churn [5]. Utilizing the logistic function, this technique enables the estimation of the probability that customers will switch providers based on various independent variables, including demographics, usage patterns, and service preferences [6]. To inform strategic decision-making processes within the telecommunications business, the model estimates the probability of customer turnover by using logistic regression. By utilizing this research, it is hoped to develop a robust prediction model that can identify clients likely to leave, thereby enabling telecom firms to grow sustainably and enhance their churn control strategies.

Companies tried to understand the reasons behind low churn rates and developed proactive action plans to solve these problems [7]. Companies may strategically employ machine learning-based customer churn forecasting models to ascertain whether a particular client is likely to leave the company ahead of time, and take the necessary steps promptly in customer churn prevention [8]. Most studies on customer churn prediction during the last few decades have concentrated on the banking and telecoms sectors. When a company faces difficulties these days, the issues are sufficiently detailed to ascertain the procedures that will be employed to resolve them. Next, the best-fit model (test set) is determined by gathering and analyzing pertinent data. Once this model has been established, data (from the validation set) pertinent to the issue statement is used to test and validate it. The required activities are then guided by a few approaches that are derived from these models [9], [10]. The entire process of identifying a problem and devising a solution is referred to as data mining. Nevertheless, the methods, instruments, and procedures used to gather, assess, and create a model, as well as the testing of these models on data, and the validation of the results [11], [12].

Numerous algorithms have been investigated in earlier studies to obtain high accuracy in forecasting customer attrition in the telecom sector [13], [14], [15]. Numerous algorithms, including decision trees, logistic regression, artificial neural networks, and support vector machines, have been extensively studied by researchers. Some studies have even ventured into employing hybrid algorithms, which combine multiple techniques to enhance predictive capabilities [16]. One common challenge encountered in these studies is the availability of limited data for predictive tasks. Despite this constraint, researchers have made significant progress in developing robust churn prediction models [17]. However, It is important to remember that the caliber and volume of data that are accessible might affect how successful these models are.

In our project, we aimed to address these challenges by leveraging a dataset containing comprehensive information about employees [2]. Unlike some previous studies that may have been constrained by data availability, our dataset provided a solid foundation for analysis. Furthermore, we focused our efforts on utilizing logistic regression, a well-established algorithm known for its simplicity and interpretability. By employing logistic regression, this study aimed to contribute to the growing body of research on customer churn prediction in the telecom industry, seeking to develop a predictive model that strikes a balance between accuracy and interpretability. The goal of this research is to develop a prediction model that will enable telecom operators' customer retention managers to refine their existing processes, specifically identifying which customers are more likely to leave their network and developing targeted retention strategies for them.

II. Materials and Methods

Data mining is the process of extracting valuable data structures from a data source. A tree, a network or graph, a set of rules, one or more algorithms, and many other elements might be included in the framework. The information obtained from a data mining session is known as a generalized data model. Applying novel scenarios to previously identified models is the ultimate goal. According to SAS in Institute 1998, data mining is the act of choosing, examining, and modeling vast volumes of data to identify and establish distinct, unidentified patterns [18], [19]. When firms have challenges these days, the issues are clearly stated so that the appropriate tools may be used to address them [2], [20].

After that, problem-related data is gathered and examined to map out the best-fit model (test set). Once this model has been identified, it is evaluated and verified using a collection of data (the validation set) related to the stated problem. Then, using these models, a few methods are developed for the required actions [21]. Data mining is the process of identifying the issue and working through it until a solution is found. However, machine learning refers to the methods, procedures, and tools used to gather data, analyze it to create a model, test these models using the data, and validate the outcomes. Data mining procedures are shown in Figure 1.

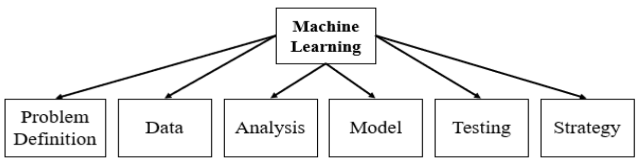

Fig. 1 Data mining processes

The objective of machine learning is to find an efficient model that suits the issue with the least amount of loss. This empirical and iterative approach necessitates training several models (test ideas) [22]. As a result, machine learning (ML) is a branch of artificial intelligence (AI) that enables computers to extract meaningful knowledge from data.

Forecasting the rate of customer attrition is crucial for maintaining a robust customer retention base and preventing significant losses across various sectors. Since there is an increasing need to predict and avoid customer turnover in many industries, several data mining and machine learning technologies are presently being implemented for this goal [23]. It is critical for businesses to effectively retain consumers to prevent significant losses, in addition to developing a reliable model that can forecast customer attrition [24], [25].

Meanwhile, the prolonged COVID-19 pandemic has heightened the importance of non-face-to-face client management and marketing across all sectors. As the amount of time spent indoors has increased, so too have the demands and interest in home appliance subscription services. In this regard, running a variety of non-in-person visiting services and using consumer-attribute-based marketing are essential. Therefore, predicting the probability of client attrition has become a crucial survival strategy in the home appliance rental sector [26], [27]. However, the home appliance rental industry offers a potential opportunity for a data-driven customer attrition prediction modeling study [24]. Class imbalance issues and the prediction performance of classification algorithms are the two key technical hurdles.

To predict customer churn, researchers used single categorization techniques in the past [28]. Algorithms for ensemble-based classification have recently been created. Liu et al [23] suggested an ensemble learning technique for forecasting client attrition that fully incorporates clustering and classification techniques [29]. A class disparity in the forecast of customer churn is another issue. For this, prior studies have mostly employed the Synthetic Minority Over-sampling Technique (SMOTE). Recently, hybrid resampling strategies have been proposed as a more effective method for handling imbalanced data. To calculate the rate of client attrition. Kimura recommended SMOTE-ENN and SMOTE Tomek-Links, two hybrid resampling approaches. These methods are creative and effective. Churn prediction studies use both traditional machine learning algorithms and deep learning approaches to show outstanding prediction ability in this non-contractual setting, where it is crucial to identify who is likely to churn [30].

In the retail sector, Seymen et al. [31] forecasted customer turnover using a deep learning algorithm on a dataset of grocery store transactions and contrasted the outcomes with those of other popular churn modeling methods. In order to assess attrition in the retail business, Dingli, et al. [32] compared two deep learning algorithms: the convolutional neural network and the restricted Boltzmann machine. Some studies simulate churn prediction using deep learning approaches, but not in non-contract cases. Using a multivariate temporal model for daily activity, Alboukaey, et al. [33], introduced a daily churn prediction technique. The use of CNN, RFM, and statistical models was also used to a dataset on mobile communication.

III. Result and Discussion

To improve accuracy and identify an appropriate model to address the issue, machine learning is an empirical and iterative process that involves training multiple models.

A. Dataset

Using behavior analysis to predict client attrition, the customer ID, or primary key, was a unique string of characters that included letters, numbers, and other characters. Customer ID and the different variables were found to be mutually dependent (one-to-many connection). Customers were divided into two unique gender categories: male and female. Before being supplied to any of the algorithms, A discrete value was assigned to the end of these groups (male, female). Since senior citizen is composed of two distinct (binary) values—a client who is over 65 is considered a senior citizen (valued = 1), and a client who is under 65 is considered a non-senior citizen (valued = 1)—no further scaling of this variable was necessary. Married customers were categorized as "Yes" and unmarried customers as "No" when the characteristic "partner" was further scaled to binary values.

The term "dependents" was created to provide small tax breaks sporadically. It included two distinct categories, which were labelled as follows: Customers indicated as "Yes" on "someone's" tax form are considered dependent customers, whereas customers who have dependents of their own are marked as "No." These clients will see more scalability. Tenure was a feature that showed the number of months that a customer's subscription had been active on the network. A continuous numerical data set containing one-month and seventy-two-month saddle and peak points, respectively. Phone service, which was categorical data (yes or no) indicating whether consumers had active phone service or not, was another feature that could be scaled into discrete binary values. Data wrangling was employed when scaling binary values to ensure that consumers without active phone service and those who did not subscribe to multiple lines received the same treatment. Customers with numerous lines were divided into two groups: those without phone service and those with various lines. Internet service shone out among the six criteria with "one to many relationships" (online backup, online security, gadget protection, tech help, streaming TV, streaming movies).

Customers may choose between fibre optic, digital subscriber line (DSL), or none of the above for this feature, which shows the type of internet service they are registered for. While the other option (NO) was treated as a distinct object during data wrangling, the DSL and fibre optic categories were treated as a single item. During data wrangling, the Yes, No, and No internet categories are handled as one entity, while the remaining categories are regarded as distinct ones. Online security refers to consumers who paid for protection against assaults while their devices remained online. These two groups defined churn, which was our dependent variable and goal value: There are two types of customers: those who did not churn (lost to competitors) and those who did. Since each label was given a binary number 1 for churners and 0 for no churners managing this characteristic was quite simple.

B. Exploratory Data Analysis

The Jupyter Notebook was used to import the Tel data dataset in CSV format from "community.ibm.com." This script was run to allow data to be imported into the Python notebook and prepared for Python exploitation.

Figure 2 below illustrates our data set's unbalanced class issue, showing a substantial discrepancy between the number of consumers who left the business and those who stayed. A bit less than 2000 clients left the network, while little over 5000 customers stayed with the networking firm.

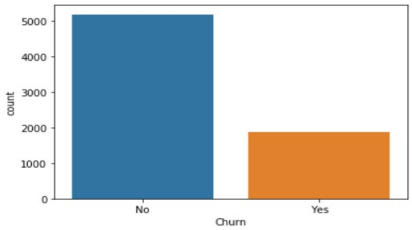

Fig. 2 Number of churners in a count plot

A bar chart showing the number of consumers who left based on their gender (male or female) may be found in Figure 3 below. According to the figure, there were significantly more customers who did not churn (more than 2,500 for each gender) than those who did (approximately 800 for each gender). Since the same proportion of consumers from both gender groups left the network, we can conclude that there is no correlation between a customer's gender and turnover.

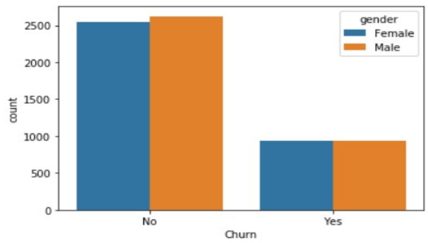

Fig. 3 The quantity of churners according to gender

Consumers without Internet service subscriptions also lacked online security, phone protection, online backup, tech support, and the ability to stream on either TV or movies. We can thus conclude that the variable, Internet Services, is a package. Additionally, some users signed up for either of the Internet Service Options (DSL or Fiber Optic) but did not have phone service (for example, for calls), and such customers used the network's phone service [34]. The 10 bar charts that follow in Figure 4 illustrate these findings.

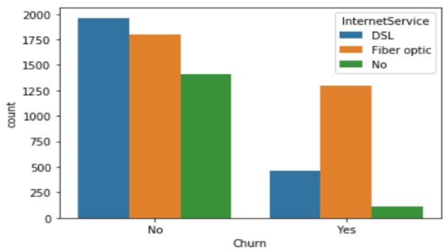

Fig. 4 Plot of customers who utilized the internet and phone service

The number of consumers who have both phone and internet service subscriptions is displayed in a bar chart in Figure 4. While more than 3000 consumers used fiber optic for both phone and internet services, about 600 people used DSL for internet access only. Based on whether they had internet access or a streaming movie subscription, Figure 5 below compares the number of consumers who left with those who stayed. Less than 250 users without internet service left the network. However, more than 1750 users who either signed up for or did not subscribe to movie streaming did not leave.

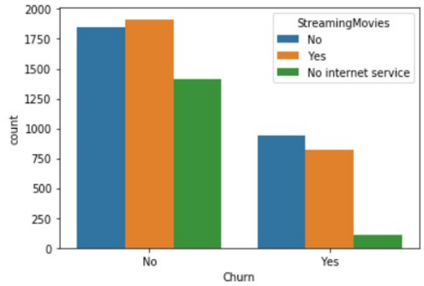

Fig. 5 Count plot for number of churners who subscribed to streaming movies

The bar chart in Figure 6 below compares the number of consumers who left based on whether they had internet service or streaming TV subscriptions. Approximately 100 subscribers who did not pay for internet access left the network, while more than 1,750 consumers who either purchased a streaming TV subscription or did not. Additionally, clients on monthly payment plans had a higher attrition rate than those on yearly or business intelligence annual subscription plans. Most churned consumers paid using electronic checks.

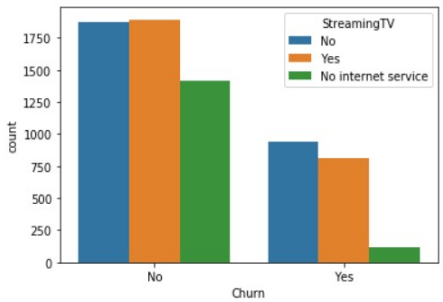

Fig. 6 Plot the number of churners who have signed up for streaming TV.

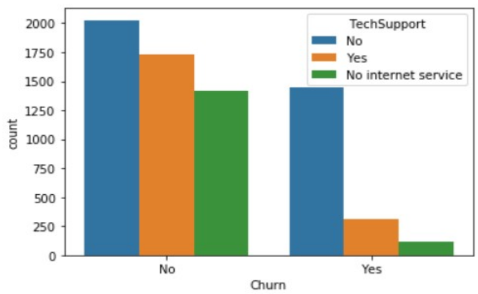

Fig. 7 The number of churners who signed up for tech help is shown

There are no "null values" (missing entries for various variables, so we could either assign values to the missing entry or remove the column if it has so many missing values that assigning values would not be a good approach The figure below illustrates that our data set is "clean" (no missing entries in any column). The Tel data set is from "community.ibm.com." Figure 7 illustrates.

Our model would function better with a clean dataset as it contains sufficient values. Figure 8 demonstrates that the dataset has no null values.

```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

Fig. 8 Number of null values

Research on predictive models for customer churn in the telecom sector offers valuable insights into a critical challenge the industry faces. In highly competitive markets where retaining existing customers is usually more cost-effective than acquiring new ones, telecom companies operate. The findings highlight the need to utilize AI and ML approaches to predict client attrition and develop targeted responses. Due to the nature of their services and client interactions, telecom businesses generate substantial volumes of data. Despite its wealth of information, this data presents challenges due to its volume, diversity, and rapid pace. It takes reliable techniques to analyze such large datasets and identify significant trends. Ineffective use of this data may result in missed opportunities to identify clients at risk and implement prompt retention strategies.

To overcome these obstacles, artificial intelligence and machine learning are essential because they automate data processing and reveal intricate patterns that conventional statistical techniques could overlook. The continual process of training and improving models gradually raises forecast accuracy. To calculate the likelihood of churn based on user attributes, this study employed techniques like logistic regression. Due to its ease of use and interpretability, logistic regression is well-suited for predicting binary outcomes, such as churn. For managers of client retention, the predictive model created in this study has significant ramifications. Telecom businesses can create targeted retention programs by precisely identifying customers who are at risk of leaving. Customers who have been classified as high-risk, for example, may receive proactive customer care, enhanced service plans, or tailored incentives. By decreasing turnover rates and promoting revenue stability, these customized approaches can strengthen client satisfaction and loyalty. Additionally, the framework clarifies the elements that lead to client attrition. Telecom companies seeking to enhance their offerings and address issues must understand these factors. Customer service experience, contract terms, price, and service quality are some standard variables that might affect turnover. Businesses can reduce turnover and increase customer satisfaction by addressing these issues.

IV. Conclusion

In conclusion, the telecoms industry's explosive growth, driven by technological advancements and increasing internet consumption, has made the incorporation of AI, along with ML technologies, imperative. These developments are crucial for enhancing security, optimizing network efficiency, and tailoring user experiences. As a fundamental component of data science and data mining, machine learning has shown exceptional efficacy in tackling important issues like churn management and prediction [34]. Telecommunications firms can identify trends, forecast consumer behavior, and develop models that enhance customer retention and operational effectiveness by leveraging big data and sophisticated algorithms. The size and complexity of client-generated data, however, continue to be significant obstacles, underscoring the need for robust analytical tools to minimize losses and enhance customer satisfaction. The model interface enables a range of activities and estimates the likelihood of churn based on the unique properties of each user.

This study clarifies the factors that lead to customer attrition in the telecom sector and offers a framework for developing effective retention tactics. By enhancing predictive performance and strengthening customer strategy, the study's conclusions enable telecom companies to become more competitive and foster long-term success. The study effectively utilized AI and ML approaches, including logistic regression, to develop a prediction model that accurately identified clients at risk of leaving, leveraging the Tel-data dataset. This enables companies to run targeted retention efforts, increasing customer happiness and loyalty. This research enhances our understanding of the factors contributing to customer churn in the telecommunications sector and provides a framework for developing effective customer retention strategies. The results are expected to enhance predictive performance and improve customer strategies for companies in this sector, ultimately improving competitiveness and contributing to sustainable growth.

The findings derived from this study indicate that utilizing machine learning techniques, such as logistic regression, can have a positive impact on telecommunication companies' ability to predict customer churn. By using the Tel-data dataset, the research effectively developed a prediction model that can precisely identify clients who are prone to churn, enabling businesses to employ targeted retention strategies to enhance client loyalty and satisfaction.

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