Research Article

Predictions of Customer's Churn in Telecommunication Industry Network Area using Machine Learning (ML) Algorithm

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Abstract

Customer churn, the loss of customers over time, poses a significant challenge for businesses across various industries. Early detection of at-risk clients enables focused actions, which in turn increases profitability and customer retention. Customer attrition is a persistent problem in the telecom sector due to intense competition. The goal of this paper is to protect revenue streams by using Machine Learning (ML) to forecast client attrition and enable tailored retention measures. Over the last ten years, various ML and data mining strategies have been published in the literature to forecast consumer churners using heterogeneity customer datasets. This paper provides an overview of the Customer turnover problem and investigates the application of different ML approaches, such as XG Boost, Gradient Boost, AdaBoost, ANN, and logistic regression, to predict customer turnover and compare the model effectiveness in terms of accuracy.

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KEYWORDS: Machine Learning (ML), Consumer Churn, Prediction Approach, Random Forest, XG Boost, G Boost, AdaBoost.

INTRODUCTION

Getting new customers is considerably more costly than sustaining the ones you already have. Retaining a current customer is less expensive by six to seven times than obtaining a new one [1]. Because they generate the majority of the profit in every industry or sector, customers are considered the most valuable assets. Nowadays, businesses are placing more of an emphasis on persuading and keeping their current clientele. If the business accurately forecasts customer behavior, strengthens the connection between customer attrition, and has control over certain circumstances, customer turnover can be decreased. You can forecast churn by analyzing the distinction between non-churners and churners [2]. Customer churn has been identified as an essential problem in a service-oriented enterprise because of its direct impact on earnings. Thus, multiple businesses concentrate on decreasing churn and discerning suitable practices. Organizations want to retain their clientele by increasing expenditures and reducing revenues. The most effective method for customer retention is to lower the churn rate, which signifies the frequency with which consumers migrate from a single company to another or discontinue use of a specific service within a given period. A variety of reasons can be identified in the past if a company examines its previous data and implements machine learning technology, which will recognize people prone to churn. [3] Nearly every company now possesses information regarding its clients and customer behavior, attributable to advancements in data management. A significant advantage of big data is the superior quality and diversity of customer information, which offers a strategic value to the organization. Data mining facilitates the identification and comprehension of consumer behavior, hence optimizing business processes and improving customer management efficacy. [4] Moreover, it optimizes the revenue per user for the corporation directly. [5] Telecommunications firms encounter a distinct issue in forecasting customer attrition. Telecom analytics is a form of business intelligence specifically designed to meet the requirements of the telecommunications industry. Telecom analytics primarily aims to optimize earnings, reduce costs, and mitigate fraud. The objective of telecom analytics is to predict, in multiple dimensions, and enhance performance. Numerous firms experience customer attrition, which impacts their earnings as clients transition from one service provider to another within the telecommunications sector. To expand their revenue-generating base, telecommunications businesses must attract new consumers while minimizing attrition. Churn analysis indicates that customers discontinue their contracts for several reasons, including superior pricing offers, more appealing packages, unsatisfactory service experiences, and alterations in their circumstances. When compared to earlier, the amount of data increased greatly. The ML model performs well but not with very large datasets. As a result, studies have been using Deep Learning (DL) approaches more recently than ML techniques, particularly for customer churn prediction, because DL techniques can handle large amounts of data. Furthermore, it maximizes the company's revenue allocated to each user directly. [5] Previous research has made an effort to comprehend client attrition. For example, a clustering and classification approach for churn control was proposed by Bach *et al.* [6]. A novel hybrid model based on ensemble and clustering classifiers was presented by Fathianetal. [8] Holtropetal's [7] goal was to use data anonymization methods to predict client attrition. While numerous research works have attempted to explain and forecast customer churn, none have attempted to predict telecom customer churn using various ML algorithms. The research paper is organized in the following manner: Section 2 examines the literature on customer turnover via the lens of machine learning, while Section 3 provides an in-depth analysis of the churn phenomenon. Section 4 delineates the proposed tasks, encompassing model development and outcome evaluation; thereafter, Section 5 articulates the conclusions drawn from the work.

LITERATURE STUDY

Kassem *et al.* [9] discerned the primary elements affecting customer attrition and pinpointed clients at risk of churning through social media analysis. The results are examined utilizing diverse machine learning algorithms, including Deep Learning, Logistic Regression, and Naïve Bayes. The primary objective of the study in [10] is to forecast customer attrition in the telecommunications sector through the application of machine learning and big data technologies. Machine learning techniques can be employed to anticipate consumer turnover. The study on consumer churn prediction utilizing KNN and big data demonstrates an accuracy rate of 80 percent for forecasting consumer churn and 1.01 percent for the area under the curve.
Ahmad *et al.* [3] developed a method for predicting customer attrition specifically for Syriatel Telecom Company. This study employed the Random Tree, Decision Tree, Extreme Gradient Boosting method, and GSM Tree algorithm. The selection and integration of components inside the mobile social network have significantly influenced the efficacy of the developed model, as Syria Tel's area under the curve (AUC) value has reached 93.301 percent. The high gradient boosting method produced exceptional results across all criteria. Almuqren *et al.* [11] introduce an innovative methodology for predicting churn and do a comparative analysis of the telecommunications sector through social media mining. This paper employed Arab Twitter mining to predict churn in Saudi Telecom companies for the first time. The method proposed in the novel is effective according to many standard criteria when compared to the actual results provided by a telecommunications operator. Multiple methodologies have been applied to forecast client attrition, encompassing data mining, machine learning, and hybrid technologies. Churn prediction and retention strategies enable firms to identify, forecast, and mitigate customer attrition. The majority employed decision trees, as it is an established technique for assessing customer churn; yet, addressing intricate issues with this method poses challenges. The research conducted demonstrates that data reduction enhances the accuracy of the decision tree. [12] Customer prediction algorithms and historical analysis are sometimes utilized in data mining. Along with the study of regression trees, decision trees, neural networks, and various other data mining techniques were explored. [13] Our technology is constructed around the analysis and visualization of data gathered from the telecommunications department. The prediction and analysis of churn using machine learning models are based on performance metrics, including precision, recall, F1-score, and accuracy.

1. CHURN PROBLEM

In the realm of commerce, customer attrition denotes the occurrence of clients switching service providers. Subscriber churn, or customer churn, is analogous to attrition when a consumer covertly shifts from one service provider to another. Churn prediction in machine learning is categorized as a supervised (i.e., labeled) problem. The aim is to project the number of subscribers who will terminate their subscription within a specified prediction horizon. Churn Prediction forecasts potential attrition before individuals exit the network. Thus, the CRM department can prevent subscriber attrition in the future by implementing retention methods aimed at attracting and retaining potential churners. Thus, the corporation would avert a possible loss. Customer attrition, or churn, is one of the most substantial expenses for any organization. The retention initiatives would be significantly improved to ascertain the reasons and timing of customer attrition with considerable precision. We will analyze the essential elements in forecasting customer attrition via a Kaggle customer transaction dataset.

Supervised machine learning aims to develop a function that maps inputs to outputs based on examples. In supervised machine learning, training data is evaluated to generate an inferred function that can map fresh instances. The telecom dataset encompasses both contemporary and historical client interactions, so this supervised classification issue aims to forecast a binary outcome (Yes/No).

Real-world churn prediction involves seven major steps: Data Preprocessing, data analysis, Model Selection, Visualization, Future Prediction, and Model Deployment.

2. PROPOSED MECHANISM

In this research, some of the answered questions will be: evaluating a crucial feature for customer turnover, which sort of customers are departing more, and which machine learning model is the best for result interpretation and prediction. As this article concludes, we'll try to address a few key business challenges regarding customer attrition:

- What are the chances of a customer leaving an organization?
- What is an organization's key indicator of churn? How can retention strategies be implemented based on our findings to reduce the number of prospective customers leaving?
- The study explored categorization techniques, comparing their performance and several metrics, including precision, recall, F1-score, and true/false positive rates. Data preprocessing involves the identification of missing values, associated variables, and outliers.
- Experimental Data Analysis for hypothesis formulation; data normalization to enhance accuracy; development of training and testing datasets; model training for cross-validation and visualization of accuracy findings from test data.

Dataset

A. This research paper uses the IBM Telecom Kaggle Dataset. The dataset encompasses several critical factors for predicted churn research and is large. The collection comprises 7,043 occurrences over 21 attributes. Features include demographic data such as gender, age, and dependents, subscription services, contract details, payment methods, paperless invoicing, monthly costs, and a variable forecasting client attrition from the prior month. The input data is in CSV format and is depicted through various visual elements, such as graphs, which aid in the detection of trends, outliers, and patterns within the data. The analysis begins with data purification, followed by graphical examination, machine learning Modeling, estimation, and outcome evaluation.

B. METHODOLOGY

The methodology or stages implemented focus of the churn prediction problem is explained in this section with a pictorial representation in figure 1.

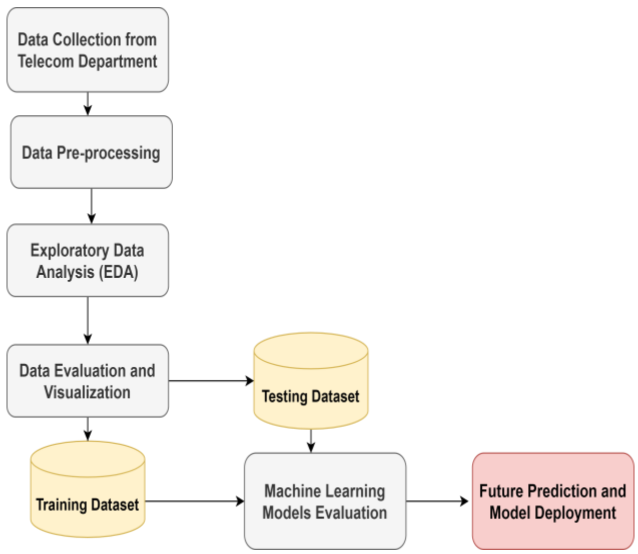

Fig. 1: Flow Diagram of various phases of Customer Churn Prediction

1. Data Preprocessing

A dataset involves features and N rows. Numerous formats are employed for values. Redundant and null values can result in diminished accuracy within a dataset and its dependent variables. Several data sources have been utilized for data collection, each employing distinct formats to denote a singular value, such as the representation of gender as Male/Female or M/F.

2. In order to eliminate noisy data, null values and erroneous dimensions, a three-dimensional image should be converted to a two-dimensional format by reducing it to binary values of 0 and 1. Images can be evaluated using OpenCV or Pandas' tabular data. Utilizing the data effectively is essential, as producing suboptimal outcomes or attaining diminished accuracy might be influenced by undesirable or null numbers. Missing and erroneous values are widespread in the dataset. A dataset with missing values may result in erroneous modeling. Consequently, the suggested methodology addresses any missing values prior to model comparison and selection. The dataset comprises 7,043 rows and 21 columns and seems to be devoid of any missing values. The complete dataset was examined, and only the most significant attributes were enumerated. The listing will achieve greater accuracy and include solely beneficial qualities by enumerating them. In a knowledge-based approach to data selection, feature selection is an essential stage. The proposed work selected aspects essential for enhancing performance and facilitating decision-making, while the remaining features are of lesser significance.

3. Data Exploration

Exploratory Data Analysis (EDA) provides a clear and improved understanding of data patterns and potential hypotheses. The distribution of attributes is essential for trend analysis of a dataset. The examination of our data set's distribution is conducted to enhance comprehension of patterns and maybe formulate hypotheses based on this knowledge. Evaluation of client distribution according to category variables: The predominant clientele of the telecommunications company possesses prepaid connections. Furthermore, Evaluation of client distribution according to category variables: The predominant clientele of the telecommunications company possesses prepaid connections. Furthermore, the number of consumers in the 1-year and 2-year contracts illustrated in Figure 2 is approximately identical. The number of consumers in the 1-year and 2-year contracts illustrated in Figure 2 is approximately identical. It appears that customers prefer electronic bill payment over bank transfer, credit card, and mail depicted in Figure 3.

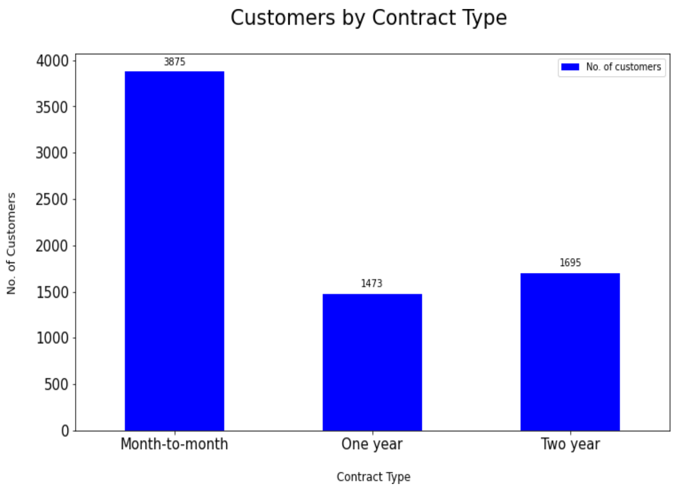

Fig. 2: Distribution of Customers by Contract Type

Figure 4 displays that nearly half of the customers have numerous phone lines. More than half of internet users stream TV and films. About 3/4 of clients prefer fiber optics and DSL. Category-based customer turnover analysis: Figure 5 shows that 74% of consumers are still active.

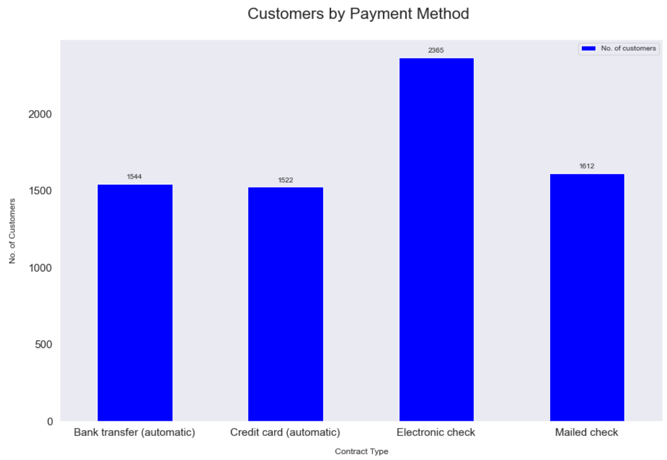

Fig. 3: Distribution of Customers by Payment Method

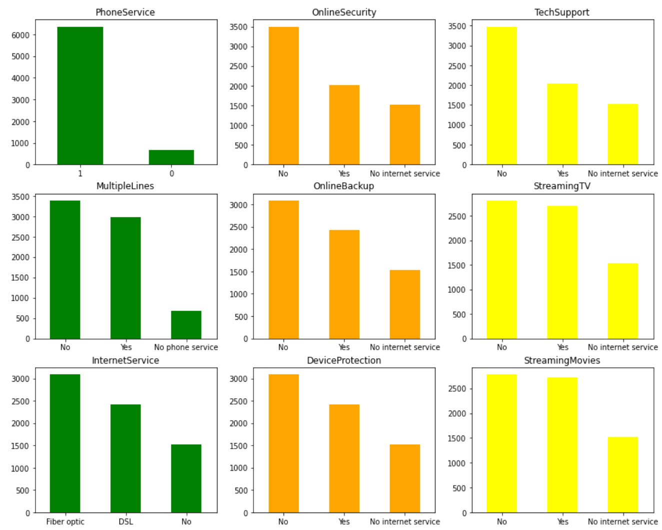

Fig. 4: Distribution of Label Encoded Categorical Variables

The figure below shows that this dataset is unequal. When each class has about equal examples, machine learning techniques work well. The dataset's skewness must be considered while using model selection metrics. Figure 6 shows that prepaid and month-to-month consumers are more likely to churn than those with 1- or 2-year contracts. Figure 7 shows that bank transfer customers have the lowest turnover rate. Figure 8 shows a positive and negative association; age and monthly charges increase churn. Churn is adversely correlated with partners, dependents, and tenure. To conclude the EDA, the dataset has no errors or missing values. Monthly Charges and Age are most positively correlated with the goal attributes, whereas Partner, Dependents, and Tenure are most negatively correlated. Most customers are active, which imbalances the dataset. The monthly and Total Charges are multicollinear. This data set contains mostly younger customers. There are many new customers in the company (less than 10 months old) and customers who have been loyal for over 70 months. According to data analysis, most customers pay between $ 18 and $ 118 a month for phone service. When customers subscribe to pay by electronic checks, they also have a very high risk of churning; they have a month-to-month connection.

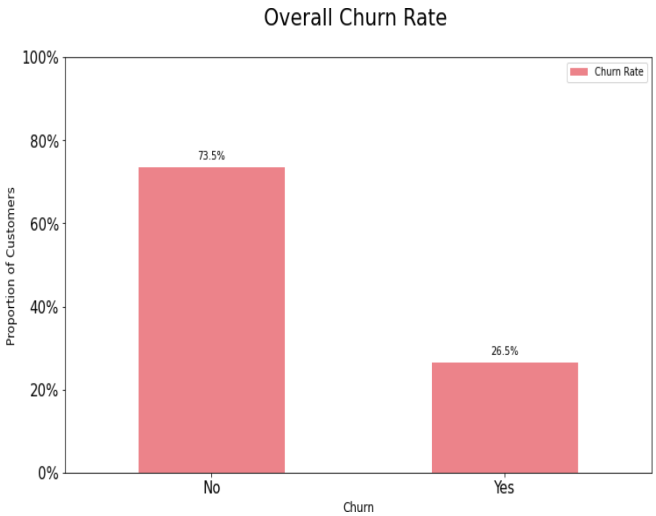

Fig. 6: Churn Rate by Contract Type

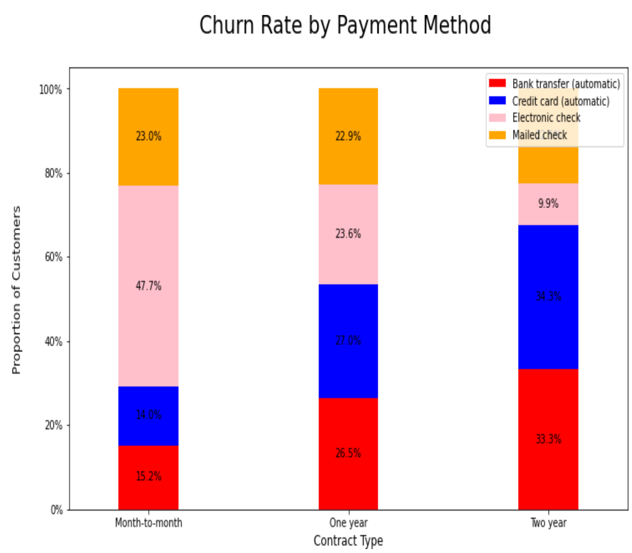

Fig. 7: Churn Rate by Contract Type

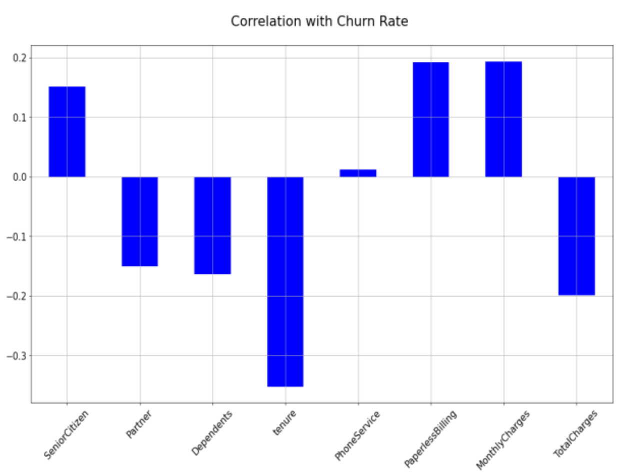

Fig. 8: Correlation with Churn Rate

3. Categorical variables with more than two values employ label and one-hot encoding. Split the data into X and Y. Y represents the 'Churn' column, and X represents the dataset's remaining independent variables. Separate the master dataset into 80% training and 20% test sets. Scaling training and testing variables from 0 to 1 is crucial before using machine learning algorithms (classification).

4. Model Selection: The classification accuracy metric is the most commonly used for comparing baseline algorithms, as it reflects the percentage of correct predictions out of total predictions. When there are class imbalances, it's not the best metric to use. As a result, let's sort the results according to the' AUC Mean', which is nothing more than the model's capability of discriminating between positive and negative classes.

Machine Learning Models

Machine learning (ML) is a branch of artificial intelligence in which software applications independently improve their predicted accuracy without explicit programming. Historical data are employed to predict the test result or output [14]. Machine learning algorithms are typically classified into three categories: supervised, unsupervised, and reinforcement learning.

Logistic regression: Logistic regression predicts target variable probabilities using supervised learning. Only two options exist since the variable of interest is dichotomous. The dependent variable is binary data that can be 0 (failure) or 1 (success). Logistic regression predicts P (Y=1) from X. This is one of the most straightforward machine learning methods applicable to several categorization challenges, including diabetes prediction, cancer detection, fraud detection, and spam detection, among others.

1. **Random Forest:** The Random Forest algorithm is a supervised learning technique utilized for classification and regression tasks. This technique is predominantly employed for classification purposes. A greater number of trees constitutes a more resilient forest. Random forests utilize data samples to construct decision trees and make predictions. Ultimately, they cast their votes on the optimal solution. Averaging mitigates overfitting.
2. **AdaBoost:** Adaptive Boosting is an Ensemble Method used to enhance neural networks. One of several. Since weights are re-assigned, Adaptive Boosting gives incorrectly categorized instances higher weights. Boosts reduce bias and variance in supervised learning. Learners progress sequentially in the system. Except for the first, successive learners grow from prior ones. Simply put, weak learners become strong.
3. **Gradient Boost:** Combines many decision tree forecasts into a single prediction. Remember that gradient boosting machines only use weak learners. Different nodes in each decision tree consider different factors to choose the optimum split. Since each tree is unique, it can catch different data signals. New trees also fix mistakes. Thus, each decision tree builds on its predecessors' mistakes.

Gradient boosting machine algorithms create trees progressively.

4. **XG Boost** is a decision tree-based ensemble machine learning technique that uses gradient boosting. It solves regression, classification, ranking, and user-defined prediction issues in unstructured data prediction (pictures, text, etc.)
5. **SVC:** A Gaussian kernel translates data points from a data space to a high-dimensional feature space using the Support Vector Clustering algorithm. Feature space searches for the smallest sphere with the data image. Mapping the sphere back into data space creates a contour around the data points. Cluster boundaries are set using this contour. Points encompassed by contours form a cluster. SVC and other non-parametric clustering algorithms make no assumptions regarding cluster size or shape. High-dimensional data requires pre-processing with principal component analysis because it works better with low-dimensional data.
6. **Guassian NB:** In general, the Bayes Theorem describes the likelihood of an event based on prior knowledge of the conditions that pertain to the event. As a result, it perfectly fits machine learning analysis since that's exactly what ma-machine learning does: making future predictions based on experience. A variant of the Naive Bayes method known as Gaussian Naïve Bayes considers Gaussian normal distributions continuous data. In machine learning, Naïve Bayes algorithms are supervised algorithms based on Bayesian theorems. This is a simple classification technique that is highly effective and functional.
7. **SVM:** Supervised Learning algorithms like Support vector Machines are widely used for classification and regression problems. Machine Learning uses it, however, primarily for Classification problems. The SVM algorithm aims to create a segregated boundary or line that can group n-dimensional space into classes to put new data points into their correct categories in the future. A hyperplane represents this boundary. In SVM, extreme points/vectors are used to create a hyperplane. Support vectors represent these extreme cases, and therefore, a support vector machine algorithm is defined.
8. **KNN:** The K-Nearest Neighbor algorithm is a simple algorithm of Machine Learning based on Supervised Learning. By assuming a similarity between new and existing cases, the algorithm places the new case into the category most similar to the existing ones. By comparing all data points, the algorithm classifies a new data point. In this way, it can be categorized in the best way possible with the KNN algorithm when new data appears. In principle, the algorithm can be used both for regression and for classification, but it is most often used for classification problems. Non-parametric algorithms, like KNN, make no assumptions about underlying data. In the training phase, algorithms just store datasets and classify them based on the previous dataset.
9. **Decision Tree Classifier:** Decision trees address classification and regression problems. This method displays feature-based split predictions in a tree-like flowchart. After a root node decides, leaves decide. Decision tree-based machine learning algorithms are crucial for predictive modeling.
10. **ANN:** The artificial neural network (ANN) is the foundation of deep learning. ANNs can handle big datasets and complicated Machine Learning issues, including image classification, speech recognition, and video recommendation due to their versatility, adaptability, and scalability. ANN algorithms select ideal weights and bias terms to minimize error [15].

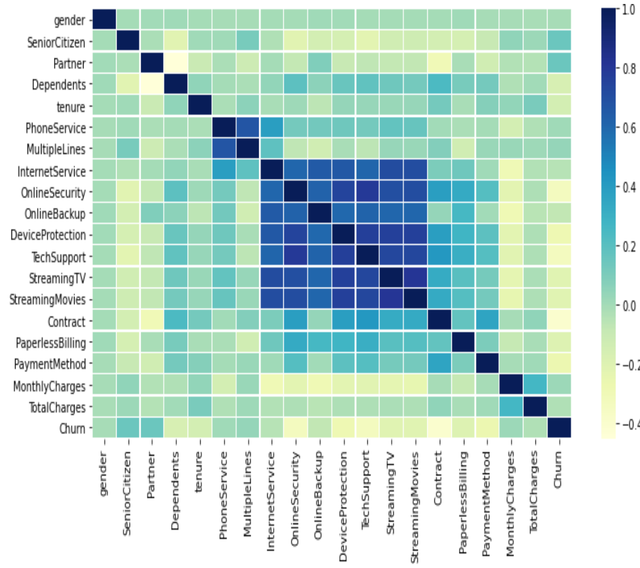

Fig. 9: Correlation Matrix

The Confusion Matrix displays the quantities of True Positives, True Negatives, False Positives, and False Negatives in a prediction. The expected number of customers who will ultimately default is likewise classified as defaulting.

The number of clients anticipated not to default is also classified as non-default.

FP: The quantity of clients anticipated to default but who will not ultimately default.

FN: The number of clients forecasted to default who subsequently do default a telecommunications firm requires insight into which clients are likely to default. Consequently, the quantity of False Positives (FPs) is minimised to ensure that the assessment of riskier clients does not overestimate their risk. All these criteria must be taken into account while evaluating the categorisation models. 'Accuracy' is the most straightforward performance metric, defined as the ratio of correctly predicted observations to the total observations. One may readily presume that the optimal model is the one exhibiting great accuracy. Accuracy is indeed a significant statistic, but it is only applicable when dealing with symmetric datasets that exhibit reasonably balanced rates of false positives and false negatives. Consequently, it is necessary to assess the model's performance by examining additional parameters. Hence, this is necessary to determine the model's performance by examining additional parameters.

$$Accuracy = \frac{(\mathrm{Tp+Tn})}{(\mathrm{Tp+Fp+Tn+Fn})} \ldots\ldots\ldots\ldots (1)$$

RESULT ANALYSIS

Performance Metrics: Correlations illustrate the relationships between variables. The target variable can be predicted using these feature variables. Statisticians employ correlation to ascertain the relationship between the variations of two variables. A correlation is a statistical method that assesses the relationship between the movements or changes of two variables.

Precision: It is the percent of positively predicted observations among all predicted positive observations. This metric answers the question, how many of all passengers that were labeled as survivors survived? Precision is related to a low false positive rate.
Correlation matrices show several variables and their "correlations." Columns and rows.

$$Precision = \frac{\mathrm{Tn}}{\mathrm{Tp+Fp}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Each value in this matrix represents a correlation coefficient between variables shown in Fig 9.

Sensitivity (Recall): Recall is measured by how many of the correctly predicted positive observations have occurred in the class - yes.

$$Recall = \frac{(2\times\mathrm{Precision}\times\mathrm{Recall})}{(\mathrm{Precision+Recall})} \ldots\ldots\ldots\ldots (3)$$

The F1 score is calculated from the aggregation of Precision and Recall. This score considers both false positives and false negatives. Although F1 may not be as intuitively understandable as accuracy, it is typically more beneficial than accuracy when addressing imbalanced class distributions. True positives and false negatives entail similar costs regarding accuracy. Precision and recall should be assessed alongside the expenses related to false positives and false negatives.

$$F1-Score = \frac{(2\times\mathrm{Precision}\times\mathrm{Recall})}{(\mathrm{Precision+Recall})} \ldots\ldots\ldots (4)$$

AUC measures the ability of a classifier to distinguish between classes, and it serves as a summary of ROC curves. A higher AUC indicates better discrimination between positive and negative classes.

Model Comparison: Machine learning methods were applied to the dataset to conduct many trials on the proposed churn model. The findings were analyzed concerning precision, recall, F1-score, and accuracy metrics. Table 1 delineates the performance outcomes of all models according to the specified measures.

Table 1: Model Analysis

ML Models	Accuracy (%)	Precision	Recall	F1-Score	AUC-Score (%)
XG Boost	84.20	0.86	0.85	0.86	86
ANN	82.98	0.89	0.84	0.85	83
Gradient Boost	82.41	0.86	0.88	0.89	85
AdaBoost	81.59	0.87	0.87	0.88	84
RF	81.10	0.76	0.79	0.76	85
LR	80.29	0.78	0.76	0.70	84
SVC	79.99	0.78	0.79	0.78	84
SVM	79.98	0.80	0.78	0.79	80
KNN	77.34	0.78	0.79	0.77	78
DT	75.56	0.78	0.80	0.79	68
Guassian NB	74.89	0.77	0.76	0.77	81

The results are tabulated in Table 1. XG Boost, Gradient-Boost, AdaBoost, and ANN give the best results in all the metrics. RF and LR are the most suitable models with higher accuracy than other models, apart from the boosting model and ANN.

Feature Importance

By means of Logistic Regression, the proposed work identifies the key factors that influence predicting the target attribute (Churn in this case). According to the logistic regression model, churn ates would be positively impacted by month-to-month contracts, fiber optic internet service, electronic checks, inept payment security, and poor tech support. In contrast, the model predicts that churn is negatively correlated with the number of customers who have subscribed to online security, an annual contract, or have mailed checks as their payment method. The feature importance is depicted in Fig. 10.

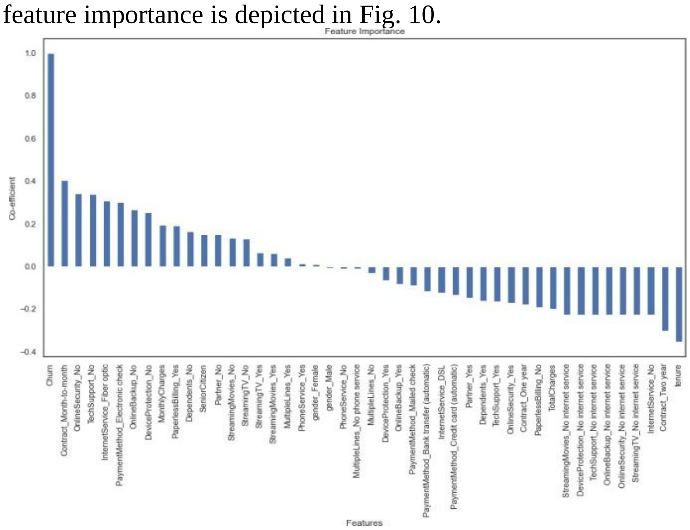

Fig. 10: Feature Importance

Future Prediction and Model Deployment

A machine learning model is improved by selecting the best parameters for it. Basically, a machine learning model has two types of parameters - the first type is the parameters that the model learns; the second type is the parameters that are found by running the model. Parameter tuning techniques such as random search or grid search are used to optimize these values that are not determined by the data and are called hyper-parameters.

Predictive models are always accompanied by uncertainty and risk. Thus, in the real world, it is important to compute both a propensity score and a predicted outcome. An additional layer of propensity score could be assigned to every 'Customer ID' rather than just presenting a binary estimated outcome (0 or 1). Last but not least, the model is deployed to the server using the 'joblib' library to build the end-to-end machine learning framework. Our model can be run over any new dataset in the future to predict the likelihood of churn for any customer.

CONCLUSION

As the telephone industry expands, the issue of client churn has also escalated significantly. Customer retention poses a significant challenge in the telecommunications sector, as it diminishes turnover by enhancing customer happiness. Predictive analytics can address this problem by detecting at-risk clients and executing customer-focused retention strategies. The suggested predictive analysis can be addressed using machine learning algorithms. The paper describes the problem of churn and the importance of preventing the same. The paper investigated the realm of machine learning methods and applied them to the dataset. For the churn prediction problem, the ensemble learning techniques that are Ad Boost, Gradient Boost, XG Boost, and ANN classifier achieve maximum accuracy, precision, recall, and F1-Score compared to other models. With the emergence of new concepts and frameworks in reinforcement learning and deep learning, machine learning will be one of the most efficient ways to address customer churn problems with more efficiency. The model is expanded to encompass additional facts from the telecommunications sector and employs approaches to attain improved outcomes in future endeavors. Big-data analytics utilizing a machine learning approach can be applied to the datasets.

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