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Exploring Customer Churn Patterns in the Telecommunication Industry: A Comprehensive Analysis

Samiksha Khandelwal,[a]. Tanya Verma,[b]. Vidit Jaiswal, [c]. Abhinav Gautam, and [D]. Dr.. Jaishree Jain[a)] Yogendra narayan Prajapati [E]

CSE Department, Ajay Kumar Garg Engineering College, Ghaziabad

(*Electronic mail: samikshamau5678@gmail.com) (*Electronic mail: tannyaverma086@gmail.com) (*Electronic mail: jaiswalvidit23@gmail.com) (*Electronic mail: gautamabhinavgautam@gmail.com) (*Electronic mail: jainjaishree@akgec.ac.in,ynp1581@gmail.com)

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In the telecom industry, massive amounts of data are being generated due to the increasing population. Business analysts assert that the expense of acquiring new customers surpasses that of retaining existing ones. The growing population issue has contributed to customer churning. This has raised concern for businesses as they need to compete passionately to retain customers as customers play a vital role in the revenue of a company. If the rate of acquiring new customers fails to match the needs of enterprise development, the collapse of the enterprise is sure, thus early detection of churning aids in taking protective measures for a company to reduce the losses. To determine the optimal choices for anticipating customer attrition before it occurs, this study assesses machine learning methods. The paper discusses capabilities, methodology, results, and ap plications. Principal component analysis is used in conjunction with decision tree and random forest algorithms for classification in the system. This allows the system to study the patterns of customer churn and various factors affecting the trends and patterns. Customer Churn Pattern analysis has the potential to rad- ically change telecommunication industries' interactions with customers. It has the features to provide better visual patterns on the trends of churning. Feature selection techniques like information gain and correlation analysis among variables are utilized to identify crucial features. These qualities have aided in several domains like businesses, banking, and insurance.

Index Terms—Customer Churn Analysis, Decision Tree Clas- sifier, Random Forest Classifier, Principal Com- ponent Analy- sis(PCA), Machine Learning (ML), EDA, Customer Retention, Telecom Industry, Churn Prediction Model and Customer Rela- tionship Management(CRM).

I. INTRODUCTION

A loyal customer base is crucial to the growth of any busi- ness. They can help businesses become more competitive in their core markets, lower the cost of publicity and negotiating, and use the herd mentality to draw in more new clients. Many businesses focus solely on acquiring new consumers while ig- noring how to retain existing clients. Research indicates that businesses will benefit more from their current customers the longer they stay in touch with them. M. Zhao et. al.[1] have pinpointed the distinguishing features of customer churn be- havior within the telecom sector. Their research delves into identifying potential churned customers within the customer base, enabling enterprises to implement tailored strategies to win them back based on these characteristics. The market for current clients is not only less expensive, but they are also more inclined to experiment with new goods.[2],[3] Accord- ing to research, your current customers spend 31% more than new leads and are 50% more inclined to check out a new prod- uct. Merely increasing client retention by 5% can yield sub- stantial benefits. There may be a 25% to 95% increase in the net present value of your clientele.Thus, one of the most important functions of customer attri- tion is that it will help the business financially. The telecom industry is not the only one experiencing churn issues. Nu- merous issues with client attrition also affect the gambling and tourist industries. When it comes to video games, players who find a game too challenging are likely to churn, or quit, while those who find a game too simple will likely become bored and eventually stop playing it.[4] Let's examine the cause of client attrition and the necessity of its analysis:

1. Tougher Telecom Environment: Due to a small num- ber of well-rounded market players' dominance, the market is saturated, and fierce price wars result.
2. Smarter and more exacting clients: Comparison shop- pers become less devoted and raise their expectations for bet- ter services at lower prices.How can we use the data currently available on customer turnover to forecast the impending departure of telecom in- dustry high-value clients? This paper delves deeply into this important problem. To meet the previously described difficulty, businesses must precisely predict the behavior of their clients.[5] There are two approaches to managing client turnover: (1) Reactive and (2) Proactive. When a customer requests to cancel, the business presents them with alluring alternatives to ensure their continued patronage.[6] Anticipat- ing customer attrition, tactics are provided to customers before

[a)]http://www.Second.institution.edu/~Charlie.Author.

any real churn occurs. Due to the rising prevalence of con- sumer churn prediction as a research topic, telecom providers have used tactics to categorize prospective churn customers according to their past behavior and records, and then provide them with offers of services to persuade them to stay.[7]

For the telecom sector, this paper presents a revolutionary churn prediction methodology. Information gain and correla- tion analysis are two feature selection strategies we used to make sure the model focuses on the most important elements. Next, using two sizable telecom datasets, we compared a num- ber of machine learning techniques for the purpose of identi- fying churning and non-churning users[8]. The Random For- est algorithm performed notably better in terms of accuracy than the others.How can we use the data currently available on customer turnover to forecast the impending departure of telecom industry high-value clients? This essay delves deeply into this important problem.

II. LITERATURE REVIEW

Under this section, some already done works are listed detecting customer churn in the telecommunication industry. Each work comes with its disadvantages and advantages.

Shivani Vaidya et al. [9] proposed a paper on customer churn prediction in the telecommunication sector, which was a brief study of various research papers on the same topic. The pro- posed paper was a brief analysis of different authors' work on churn analysis. This paper mainly aims at two points: min- ing techniques and publication year. The paper pointed out feature selection is mostly used in data preparation methods followed by Normalization and Noise removal. It stated that imbalanced, large, and high-dimensional datasets are central difficulties in telecom churn prediction.

Fatih Kayaalp [10] explored the prevalence of customer/user behavior analysis in institutions and organizations, highlight- ing the importance of crafting plans informed by such anal- yses. It is proposed that further research endeavors focus on developing hybrid models incorporating individuals' interac- tions with users in their social networks, which may yield more accurate estimation outcomes.

Sulaiman Olaniyi Abdulsalam et al. [11] use the selection algorithm of a Relief-F function with Random Forest and CNN classifiers to predict several customers who will exit from the telecom company. The results of experiments show that Relief-F-CNN does a better job of generalization when it comes to predicting churn rate with a high level of accuracy than Random Forest. This study is limited to credit risk data and can be adopted by larger datasets with further optimizers and classifiers.

Irfan Ullah et al. [12] introduced a model designed for data analytics that addresses customer churn, which was validated using standard evaluation metrics. Our findings reveal that machine learning approaches considerably boost the effec- tiveness of customer churn prediction models.[13],[14] No- tably, Random Forest and J48 algorithms yielded a superior F-measure result of 88%. The main churn factors were identi- fied in this paper and cluster profiling was performed depend- ing on their risk of churning.

Abdelrahim Kasem Ahmad et al. [15]presented a brand-new big data platform-based customer churn prediction method- ology. It makes use of cutting-edge feature engineering and selection strategies as well as machine learning techniques. In assessing its efficacy, the model demonstrated exceptional performance with an impressive Area Under the Curve (AUC) score of 93.3%.[16][17] Additionally, the model includes a novel component: Social Network Analysis (SNA) elements taken from the social networks of its clients.[18],[19]. A loyal customer may provide major benefits by reducing the expense of public relations, which can lead to attracting more new cus- tomers and increasing profits.[20],[21],[22] Businesses can create focused plans to keep ahead of the competition by fore- casting the demands and behaviour of their customers. The importance of retaining old consumers and maximizing the company revenue is ignored by enterprises as they are busy finding new strategies to attract new consumers.[23],[24] As per the findings of Reichheld et al. [5], the duration of a com- pany's commercial relationship with a client positively corre- lates with the revenue generated from that consumer.

III. METHODLOGY

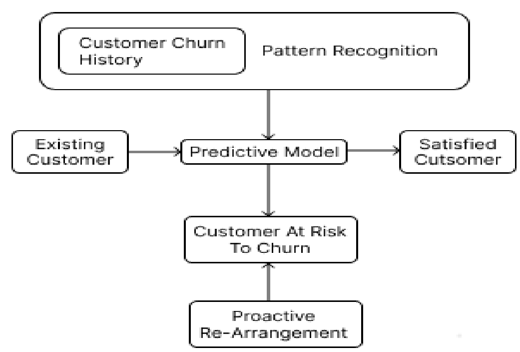

FIG. 1. Model Architecture diagram

The present study employs a hybrid methodology, integrat- ing qualitative and quantitative approaches. In the prelimi- nary phase of this study, an extensive examination of prior re- search about the recognition of customer churning and associ- ated technologies was undertaken. The purpose of this litera- ture review was to establish a solid basis for the identification of gaps, challenges, and potential solutions within the exist- ing body of research. Through an extensive examination of exist- ing literature, this review endeavors to offer a compre- hensive insight into the current landscape of knowledge within the field. Through this process, it is anticipated that valuable insights and recommendations can be derived to address the identified gaps and challenges. In the subsequent phase of our study, we adopted a quantitative research methodology, specifically utilizing the deep learning paradigm. The present study employed analyzing the data with three different tech- niques i.e. Decision Tree classifier, Random Forest classifier, and Principal Component Analysis. The utilization of these particular methodologies enabled us to effectively train the model in the identification and interpretation of complex pat- terns present in the data of the customers. As a result, we have established a recognition system that is both com- prehensive and proficient in its ability to accurately discern and under- stand the nuances inherent in trends of customer churning.

A. Customer Data :

The data has been gathered from reports published by di- verse telecommunication sectors, providing crucial insights from the industry's standpoint within a real-time setting. These insights pertain to essential factors influencing a con- sumer's decision regarding the utilization of services offered by a specific telecommunication company.

Wide-ranging experiments have been done by many data ana- lysts and scientists that have been uploaded on public websites such as Google Dataset Research and Kaggle. So, the dataset used in this paper has been imported by Kaggle which con- tains an imbalance of values along with some missing values which have been rectified in the data cleaning and EDA sec- tion. Initially, our dataset was comprised of 21 columns and 7043 rows. After performing EDA, it was converted to 51 columns and 7043 rows.

B. Exploratory Data Analysis(EDA):

Exploratory Data Analysis (EDA) involves condensing data through diverse charts and graphs to uncover patterns within the dataset. Its purpose is to scrutinize and detect trends, ul- timately aiding in the visualization of patterns, trends, and in- sights crucial for analysis and model development.

```
In [7]: # Checking the data types of all the columns
        telco_base_data.dtypes

Out[7]: customerID          object
        gender              object
        SeniorCitizen        int64
        Partner             object
        Dependents          object
        tenure               int64
        PhoneService        object
        MultipleLines       object
        InternetService     object
        OnlineSecurity      object
        OnlineBackup        object
        DeviceProtection    object
        TechSupport         object
        StreamingTV         object
        StreamingMovies     object
        Contract            object
        PaperlessBilling    object
        PaymentMethod       object
        MonthlyCharges     float64
        TotalCharges        object
        Churn               object
        dtype: object
```

FIG. 2. Datatypes of various features

As seen in figure 2, the information about data types has been known through EDA, and can be seen that the dataset consists of 3 numerical values i.e. Tenure, Monthly charges, and Senior Citizen.

As seen in figure 3, to get an insight into the numerical dataset describe function has been used. After analyzing the above ta- ble three key insights have been uncovered.

```
In [8]: # Check the descriptive statistics of numeric variables telco_base_data.describe()
Out[8]:
```

	SeniorCitizen	tenure	MonthlyCharges
count	7043.000000	7043.000000	7043.000000
mean	0.162147	32.371149	64.761692
std	0.368612	24.559481	30.090047
min	0.000000	0.000000	18.250000
25%	0.000000	9.000000	35.500000
50%	0.000000	29.000000	70.350000
75%	0.000000	55.000000	89.850000
max	1.000000	72.000000	118.750000

FIG. 3. Briefing of numerical columns

1. Senior Citizen: It appears that this group is underrepre- sented. Instead of using a 25%-50%-75% spread, categorical data usually includes counts or percentages for each group.
2. Tenure: The data on tenure may be unbalanced. 75% of customers with a term of fewer than 55 months raise the pos- sibility that the data is biassed in favour of recent arrivals.
3. Monthly Charges: There may be some irregular- ities in this data. While the average monthly fee is 64.76*, 25%o f usersspendmorethan*89.95, suggesting that a sizeable fraction of consumers have greater fees than the av- erage shows.

Given our familiarity with the target variable, we generated a bar graph illustrating the comparison between churn and non-churn customers. The accompanying figure displays this graph along with the churn-to-non-churn ratio, which stands at 73:27. This indicates an imbalance in the dataset, prompt- ing us to analyze additional features while treating the target variable separately to glean further insights.

1. Data Cleaning:

This constitutes the second stage of EDA, aimed at enhanc- ing the dataset's quality to facilitate more effective analysis and model development. The primary objective of data clean- ing is to furnish a robust dataset devoid of outliers, missing values, and extraneous columns. This endeavor significantly bolsters the accuracy of the model.

Upon examining the aforementioned figure 4, it becomes evident that there are 11 missing values present in the Total Charges column. We tested the "Total Charges" column using the IsNull() function (or its equivalent) in order to find and fix any possible problems with missing data. This feature aids in locating missing values within the data set precisely. As a result, a data frame exclusively comprising rows with missing values was generated. Consequently, these rows were elimi- nated by employing the fillna(0) function.

After resolving the missing values issue, a new column 'Tenure Group' with numerical data type was introduced.

In figure 5 the range of months is (1-12 months). It is seen that consumers having a tenure of 1-12 months are more

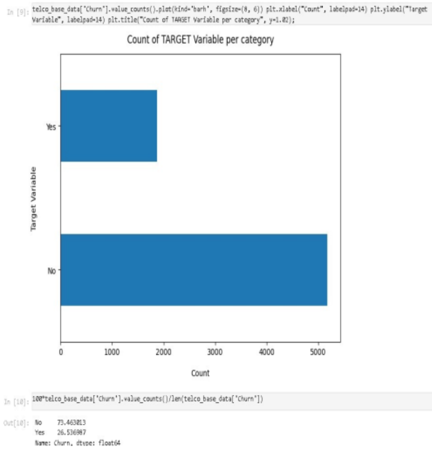

FIG. 4. churn vs non-churn ratio

```
In [22]: telco_data['tenure_group'].value_counts()

Out[22]: 1 - 12     2175
         61 - 72    1407
         13 - 24    1024
         25 - 36     832
         49 - 60     832
         37 - 48     762
         Name: tenure_group, dtype: int64
```

FIG. 5. Tenure Group datatype:int64

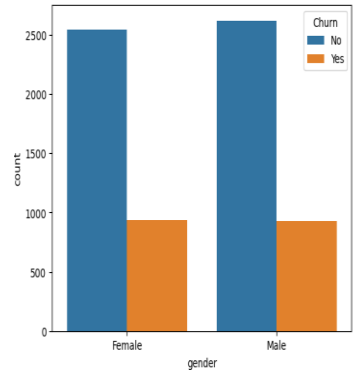

FIG. 6. Churn Count vs Gender

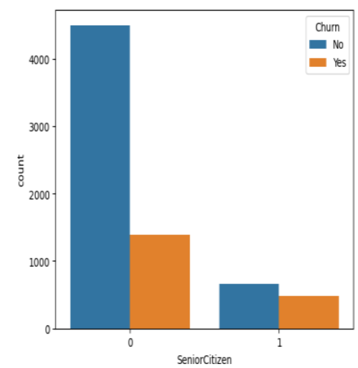

FIG. 7. Churn Count vs Senior Citizen

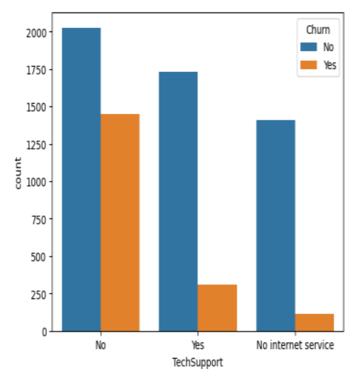

FIG. 8. Churn Count vs Tech Support

likely to churn. This makes sense because greater ties with customers are associated with a lower chance of turnover, and weaker links with customers are associated with a higher probability of churn.

2. Monovariate Analysis:

This is the third step of EDA and is a type of data exploration method. It considers each feature and the target variable (label) individually. Histograms serve as a convenient tool for interpreting various variables with ease, particularly in monovariate analysis. Below are some of the graphs commonly employed for this purpose:

There are many histograms out of which some are shown in the paper. As observed in figure 9 Churn Count vs Tenure group the 1-12 month tenure group has the highest churn ratio as compared to the 61-72 month group.
Additionally, in Churn count vs Gender figure 6, the churn ratio of both females and males is somewhat the same. There- fore, as this column doesn't provide us with any valuable in- sight into the churn trend hence it can be dropped.
Similarly, in figure 7 the churn ratio of non-senior citizens and senior citizens can be a little delusional. But if churn to a non-churn ratio is seen then it turns out that senior citizens are more likely to churn than non-senior citizens.
As seen in below figure 10, there is a linear relationship between monthly charges and total charges.

As observed in the below figure 11, it is glaringly clear that the count of churn is higher in higher monthly charges and lower in lower monthly charges.

In below figure 12, different features having correlation and targeting churn labels are listed. Three kinds of correlation

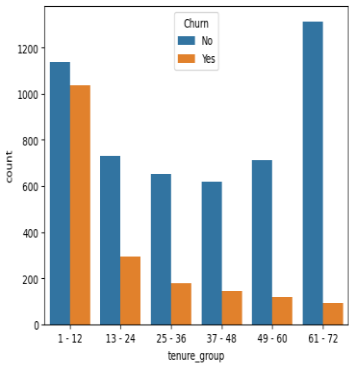

FIG. 9. Churn count vs Tenure Group

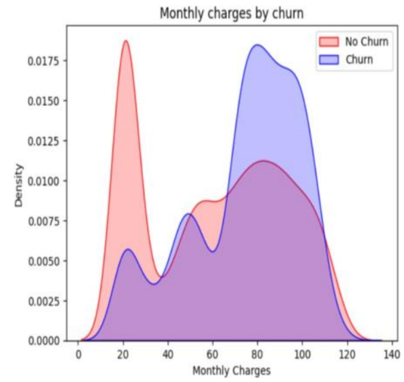

FIG. 11. Customer attrition tends to increase with elevated monthly charges

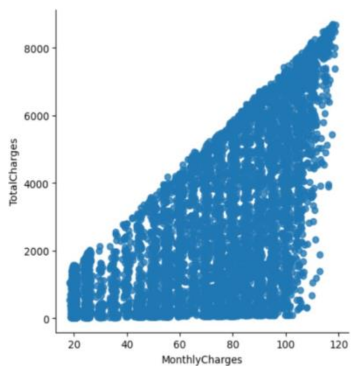

FIG. 10. Total Charges increase as Monthly Charges increase

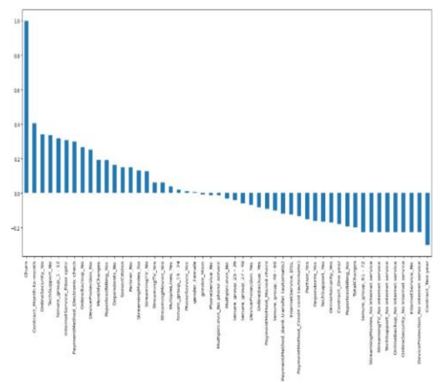

FIG. 12. Correlation Matrix

can be seen in the matrix: positive, negative, and neutral. The neutral features have a correlation score and hence can be ignored.

Customers in their first year of subscription who have month-to-month contracts, don't have tech support or online security, and use Fibre Optics Internet have significant churn rates. On the other hand, consumers with long-term contracts, subscriptions that do not include internet service, and those who have been active for more than five years exhibit low churn rates. Gender, phone service accessibility, and the quantity of lines carried have little effect on customer attrition. This conclusion is reinforced by the heatmap provided below in figure 13.

3. *Two-Dimensional Analysis:*

Contrary to monovariate analysis, two-dimensional analysis works with two variables at a time.

From figure 14, it can be confidently said that irrespective of gender, consumers are falling into the category of high churners when they have month-to-month contracts. The good news is that customers with contracts of two years or longer see a significant decrease in turnover rates. Regardless of gender, there is a persistent positive trend.

According to the data in figure 15, a few client segments are more prone to leave. Among them are women who pay using credit cards, maybe because they are worried about billing or security. Customers who use electronic checks are also more likely to churn, which could be a sign of a preference for less automated processes. Lastly, the lack of tech support services or internet security dramatically raises the chance of customer churn, perhaps as a result of irritation and discontent.

IV. DISCUSSION OF THE SYSTEM'S ACCURACY AND PERFORMANCE

A. Significant Findings from EDA

Upon conducting EDA on the dataset, several key insights emerged as highly valuable and compelling. Firstly, it was observed that for senior citizens, a categorical data type, the distribution across quartiles (25th, 50th, and 75th percentiles) is not appropriate. Secondly, higher churn rates are proportional to high monthly charges, low tenure, and low total charges. Furthermore, it was shown that high churn

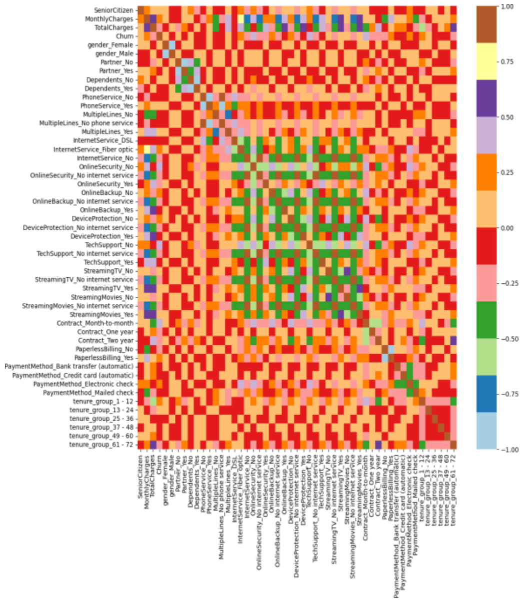

FIG. 13. Heat Map

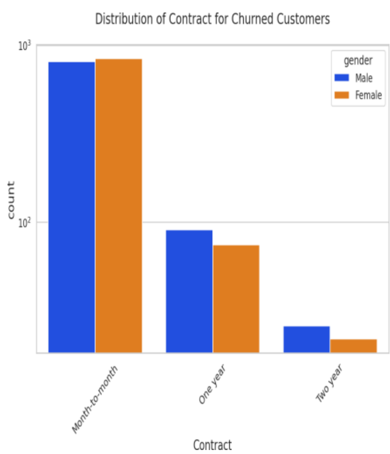

FIG. 14. Contract Type Vs Churn Count

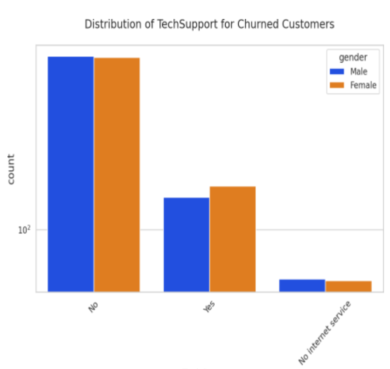

FIG. 15. Tech Support Vs Churn Count

rates were linked to month-to-month contracts, a lack of online security and tech assistance, subscriptions within the first year, and fibre optic internet access. Short contracts, the absence of services (security, tech support) in the first year, and—surprisingly—fiber optic users are identified by the study as major contributors to telecom churn. Long-term consumers with no internet service, lengthy contracts, and low turnover are the opposite. Telecom firms can use these insights to help them develop consumer loyalty. Concluding the list, it's worth noting that features such as gender, avail- ability of phone service, and the number of multiple lines have virtually no discernible impact on churn rates.

There are some impeccable insights:-

1. The medium of electronic check payments exhibits the highest churn rate.
2. Customers with monthly contracts, who have the flexibility to terminate their service at any time, tend to contribute significantly to high churn rates.
3. Non-senior citizens are found to be among the demograph- ics with higher rates of churn.

B. The Accuracy of Model

To tackle client attrition, machine learning algorithms are trained using a propensity score, which indicates the likeli- hood of a client departing soon. It is vital to identify clients who are at risk of churning (CCP). Our next section exam- ines the various stages of our churn prediction model and how different machine learning methods are utilized to attain high accuracy. Numerous algorithms, including logistic regression and SVM, were tested, among which three demonstrated the highest accuracy.

Among the Decision Tree Classifier, Principal Component Analysis (PCA), and Random Forest classifiers, the RF Clas- sifier with SMOTEENN stood out the best with an accuracy of 94.5%-95%. In the context of churn prediction, the labels 0 and 1 represent non-churners and churners, respectively. Pre- cision quantifies the accuracy of predictions, measuring the ra- tio of correctly predicted positive cases to all cases predicted as positive. Conversely, recall determines the proportion of accurately anticipated positive cases to all positive cases that actually occur. A balanced assessment of a model's perfor- mance that takes into account both precision and recall met- rics is provided by the F1 score, which is the harmonic mean of precision and recall.

Decision Tree Classifier with SMOTEENN gave an accuracy of 92%, and a very good recall, precision& f1 score for mi- nority class

TABLE I. Random Forest Accuracy Table

	Precision	Recall	F1-Score	Support
0	0.94	0.93	0.98	498
1	0.95	0.96	0.95	677
Accuracy			0.95	1175
Macro Avg	0.95	0.94	0.94	1175
Weighted Avg	0.95	0.95	0.95	1175

TABLE II. Decision Tree - Accuracy Table

	Precision	Recall	F1-Score	Support
0	0.92	0.93	0.92	554
1	0.93	0.93	0.93	626
Accuracy			0.93	1180
Macro Avg	0.93	0.93	0.93	1180
Weighted Avg	0.93	0.93	0.93	1180

While PCA gave an accuracy of 71%-72%.

TABLE III. PCA - Accuracy Table

	Precision	Recall	F1-Score	Support
0	0.69	0.62	0.65	498
1	0.74	0.79	0.77	677
Accuracy			0.72	1175
Macro Avg	0.71	0.71	0.71	1175
Weighted Avg	0.72	0.72	0.72	1175

V. CONCLUSION

As the population and digitization are vigorously increas- ing with each day, it has become a basic necessity to have a mobile phone for an individual. The increasing technological advancement has increased unspeakable competition among various telecommunication organizations.

It is a big challenge for telecommunication industries to cope with increasing customer retention along with the company's revenue. Customer retention plays an important role as losing a single customer affects the profit of a company significantly. One significant way to retain a customer while gaining some new ones can be by appointing a capable Customer Relation- ship Manager(CRM) who can take care of the issue. If a capa- ble manager takes the responsibility to retain consumers, then a consumer can never think of churning and can turn into an unconditional loyal consumer.

The conventional methods of operation within telecommuni- cation organizations are rooted in tradition and should be ne- glected. It is important to teach telecommunication industries about various new technologies such as Machine Learning and Data mining about the impeccable benefits they can provide to their organizations.

Just like CA is appointed to keep track of the spending and financial status of a company. similarly, ML engineers or data scientists must be appointed to analyze the trends and patterns in customer churning and retention. This will help them to prevent the churning and losses occurring.

Our paper has proposed a variety of algorithms like logis- tic regression, SVM, RF Classifier, Decision Tree Classifier, and PCA. Among numerous algorithms considered, only three were selected, with the Random Forest Classifier ultimately yielding the highest accuracy of 95 %. In addition to accu- racy, we've also enhanced our F1 score, Precision, and Recall, demonstrating their effectiveness.

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