Investigating Predictive Models for Data Analytics to Understand Customer Churn and Contributing Factors

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Abstract

Customer churn is a pressing concern for businesses across industries. Losing customers can lead to lower profits, reduced revenues, and potential loss of business, which can be detrimental to a company's success. As a result, it is crucial for companies to identify the reasons behind customer churn and develop effective strategies to retain their customers. One promising approach to tackling this problem is through the analysis of historical data.

By analyzing customer behavior and transactional data, companies can develop a predictive model for customer churn and identify the factors that contribute to it. In addition, this approach can also help companies identify the most profitable service types and estimate the amount of revenue loss due to customer churn. In this research study, we aim to achieve these objectives through quantitative research methods, which involve analyzing numerical data and applying statistical techniques to compare the accuracy of various prediction models. By gaining a better understanding of customer churn and its impact on business, companies can develop effective strategies to retain their customers and improve overall business profitability.

1. Introduction

In today's highly competitive business environment, customer churn is a major challenge for companies across a wide range of industries. Losing customers can have serious implications for a company's bottom line, as it leads to lower profits, reduced revenues, and even the risk of losing business altogether. As a result, it is essential for companies to identify the reasons behind customer churn and develop effective strategies to retain their customers.

One promising approach to tackling this problem is through the analysis of historical data. By examining customer behavior and transactional data, companies can develop a predictive model for customer churn and identify the factors that contribute to it. This analysis can also help companies identify the most profitable service types and estimate the amount of revenue loss due to customer churn.

The use of data analytics tools to analyze customer behavior is becoming increasingly important for companies to remain competitive in their respective industries. With the growth of digital platforms, companies now have access to vast amounts of data on customer behavior, making it possible to gain insights into customer preferences and behavior that were not previously available.

In this research study, we aim to address the challenge of customer churn through quantitative research methods. By analyzing numerical data and applying statistical techniques, we seek to compare the accuracy of different prediction models and identify the most effective strategies for retaining customers. The goal of this research is to help companies gain a better understanding of customer churn and its impact on business profitability, and to develop effective strategies for retaining customers and improving their bottom line. Overall, this research study highlights the importance of customer retention for business success and the potential benefits of using data analytics to address this challenge. By leveraging the power of data, companies can gain valuable insights into customer behavior and develop effective strategies to retain their customers, ultimately improving their bottom line and securing their long-term success in a highly competitive market.

2. Literature Review

Customer churn is a critical problem that companies face in various industries, leading to reduced revenue and profitability. To overcome this challenge, companies use historical data analysis to identify the reasons behind customer churn and develop effective strategies to retain customers. This literature review aims to provide a comprehensive overview of recent research related to customer churn prediction using data analysis techniques.

In the paper, Abdelrahim et al. (2021) [1]proposed a framework for predicting customer churn in the telecom industry using machine learning algorithms. The authors utilize a big data platform to handle the large volumes of data generated by telecom companies and apply different machine learning algorithms to predict customer churn. The study applies different feature selection techniques to identify the most important factors that contribute to churn, including customer demographics, service usage patterns, and billing information. The authors experiment with several machine learning algorithms, including logistic regression, decision trees, and neural networks, and compare their performance in predicting customer churn.

The study finds that the logistic regression algorithm outperformed other algorithms in terms of accuracy, with an accuracy rate of 91.5%. The authors also identify the most important features contributing to customer churn, including the number of service complaints, the tenure of the customer, and the type of service subscribed to. The study highlights the importance of feature selection in predicting customer churn and the need for effective strategies to retain customers based on the identified factors.

Arai et al. (2023)[2] proposed a customer churn estimation method based on LightGBM for improving sales in the telecom industry. The authors reported an accuracy rate of 93.4% for their model and demonstrated its efficiency in handling large volumes of data. Their method also outperformed traditional machine learning algorithms such as logistic regression and decision tree. They used various features such as customer demographic data, service usage patterns, and customer transaction data to predict the likelihood of customer churn. They then evaluate the performance of their method using several metrics, including accuracy, precision, recall, and F1 score. The results show that their method outperforms other machine learning algorithms such as Logistic Regression and Random Forest in terms of accuracy and computational efficiency. They also conduct a feature importance analysis to identify the most significant factors contributing to customer churn. Overall, their work demonstrates the effectiveness of using LightGBM for customer churn prediction and highlights the importance of feature engineering in developing accurate predictive models.

In the paper by Yuan (2023)[3], the author proposed a composite model for predicting customer churn in the telecom industry. The composite model is a combination of multiple prediction models, including logistic regression, decision tree, and support vector machine (SVM), to improve the accuracy of the prediction. The author used a large dataset collected from a telecom company and evaluated the performance of the composite model in terms of accuracy, precision, recall, and F1 score. The results showed that the composite model outperformed each individual model and achieved an F1 score of 0.89, indicating high accuracy in predicting customer churn. The author also conducted a feature importance analysis and found that the most significant factors contributing to customer churn were the number of complaints, account balance, and call duration. The proposed composite model can provide valuable insights for telecom companies to develop effective strategies for customer retention and improve their overall business performance.

According to Weiss and Vilenchik (2023)[4], predicting churn in online games can be achieved by quantifying the diversity of engagement. Their study focuses on the analysis of user behavior in online games and aims to identify patterns that can predict churn. The authors propose a method that quantifies the diversity of user engagement by analyzing different aspects of gameplay, such as game modes, challenges, and social interactions. They use this method to develop a predictive model for churn and evaluate its performance using a dataset of players in a popular online game. The results show that the proposed method outperforms traditional churn prediction models and provides insights into the factors that contribute to player retention in online games.

Maan and Maan (2023)[5] proposed a customer churn prediction model using explainable machine learning techniques. The authors utilized an ensemble of classifiers to predict customer churn and to identify the key drivers of churn. They used various techniques such as feature selection and oversampling to handle imbalanced data. The model was evaluated on a real-world dataset from a telecom company, and the results showed that the proposed model outperformed traditional machine learning models in terms of accuracy and interpretability. The study demonstrates the potential of using explainable machine learning models for customer churn prediction and provides insights for businesses to improve customer retention strategies.

Saha et al. (2023)[6] proposed a deep learning-based churn prediction method for the telecommunications industry. The authors utilized a combination of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to analyze large volumes of customer data, including demographic, behavioral, and transactional information. The proposed method achieved high accuracy in predicting customer churn, outperforming traditional machine learning models such as Logistic Regression, Random Forest, and XGBoost. The authors also conducted feature importance analysis to identify the most significant factors contributing to customer churn, including usage patterns, customer service interactions, and payment history. Overall, the proposed deep churn prediction method can help telecom companies to proactively identify customers at risk of churning and implement targeted retention strategies.

3. Methodology

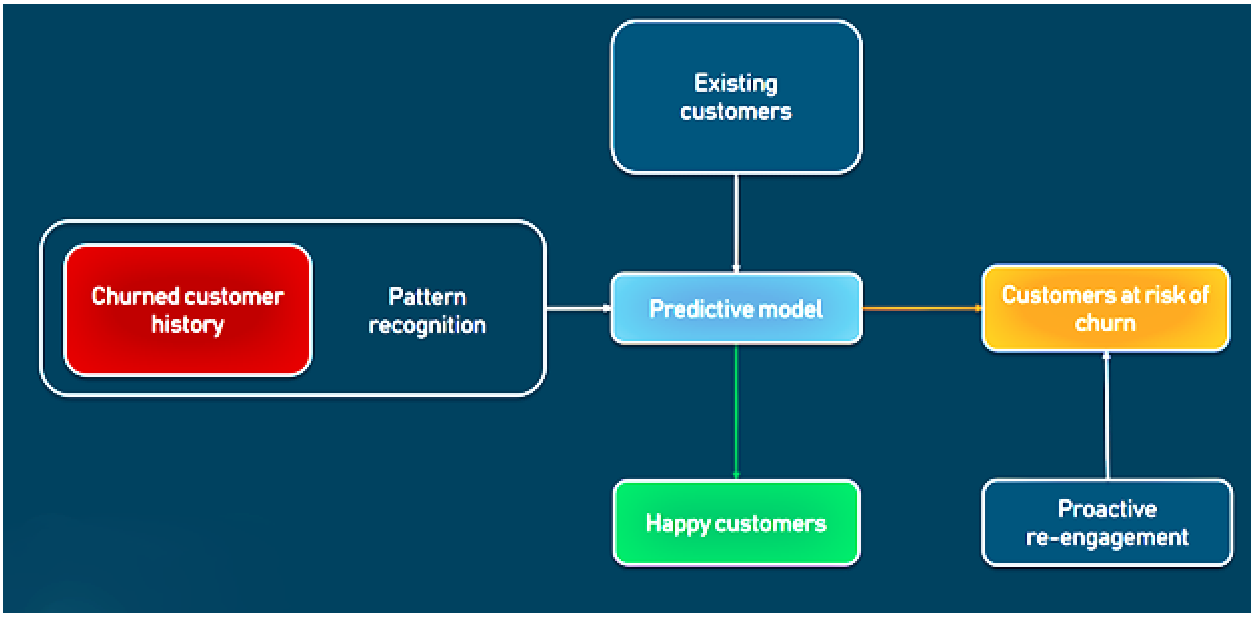


Fig 1. Churn Rate Prediction with Machine Learning an overview.

Data Collection:
The participants of this study were customers of a telecommunications company. The data set utilized for this study was obtained from Kaggle and can be accessed under the file name "WA_Fn-UseC_-Telco-Customer-Churn.csv". It includes 7043 customer records with 21 variables describing each customer's attributes, such as their monthly charges, tenure, and whether they churned.

Statistical Analysis: We performed statistical analysis on the dataset to identify potential predictors of customer churn in the telecommunications industry. Specifically, we used ANOVA and Wilcoxon rank-sum tests to examine whether there were significant differences in tenure and monthly charges between customers who had churned and those who had not.

Classification Models: To improve the performance of the data, we performed classification based on the following models: Naive Bayes Classifier, Logistic Regression, Support Vector Machines (SVM), Gradient Boosting Classifier, XGBoost Classifier, LightGBM Classifier, CatBoost Classifier, and Neural Network Classifier (using TensorFlow or Keras).

Evaluation Metrics: We evaluated the performance of each classification model using metrics such as accuracy, precision, recall, and F1-score. We also used confusion matrices and ROC curves to assess the models' performance.

Data Preprocessing: Before applying the classification models, we preprocessed the data by handling missing values, encoding categorical variables, and normalizing numerical features.

Model Selection: We selected the best-performing model based on the evaluation metrics and used it to make predictions on new data.

Data Analysis and Statistical Methods:
After cleaning and preprocessing the data, we performed an exploratory data analysis to understand the distribution of variables and their relationships with each other. We

then conducted a hypothesis test using both ANOVA and Wilcoxon rank-sum tests to investigate whether there were significant differences in tenure and monthly charges between customers who had churned and those who had not. The ANOVA test results indicated that there was a statistically significant difference in tenure between the two groups. The Wilcoxon test results showed that there was a statistically significant difference in monthly charges between customers who had churned and those who had not.

Furthermore, we performed a Tukey HSD post-hoc test to determine which specific groups differed significantly in mean values. The results of the Tukey HSD post-hoc test indicated that there was a significant difference in the mean values of tenure between customers who had churned and those who had not. Customers who had churned had a significantly lower mean tenure than those who had not churned.

Data Visualization

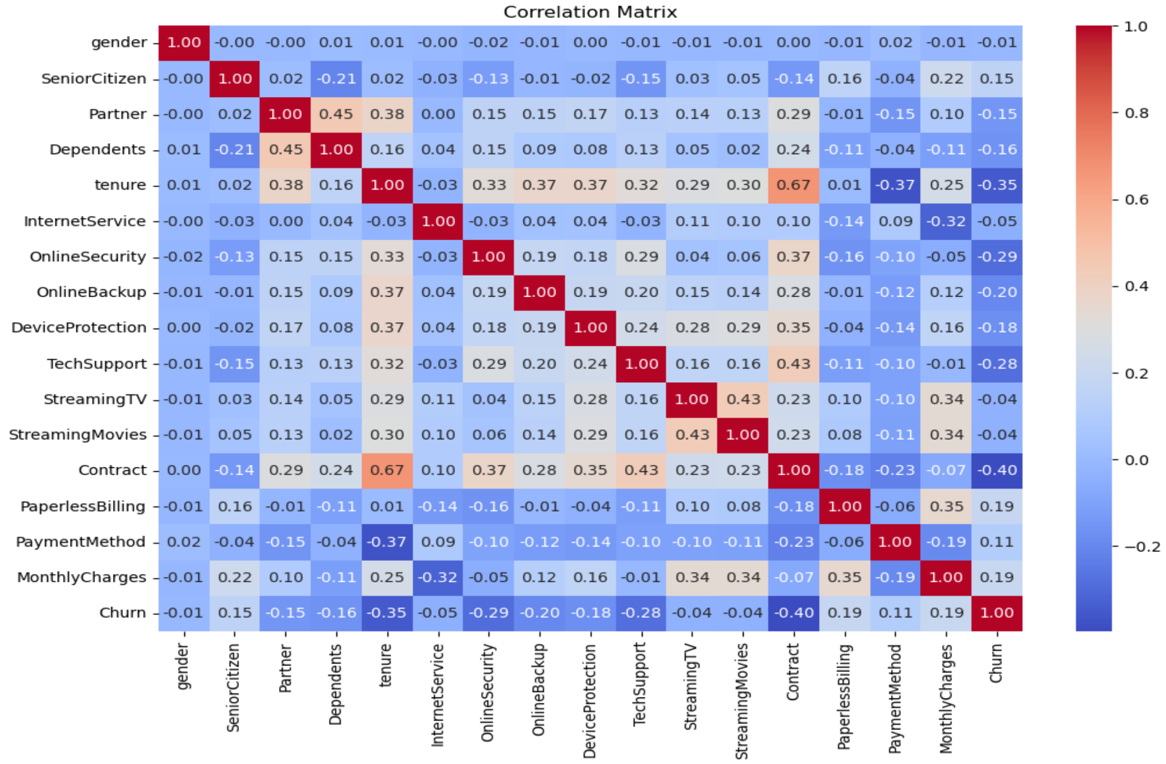


Fig 2. Correlation Matrix for Telcom dataset

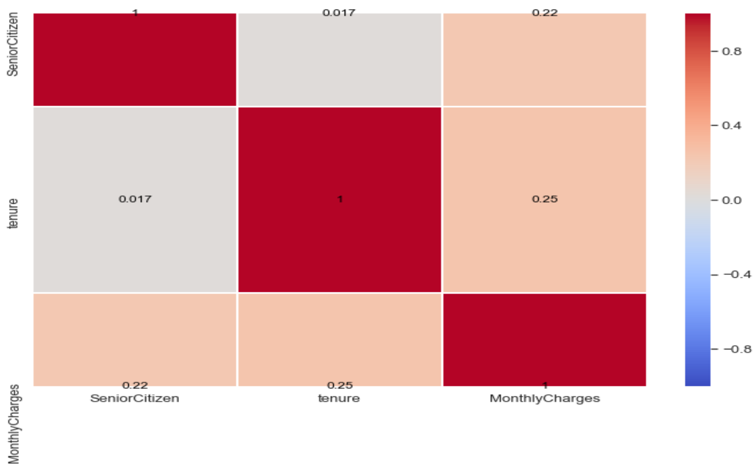


Fig 3. Correlation Matrix for Telcom dataset based on the selective features.

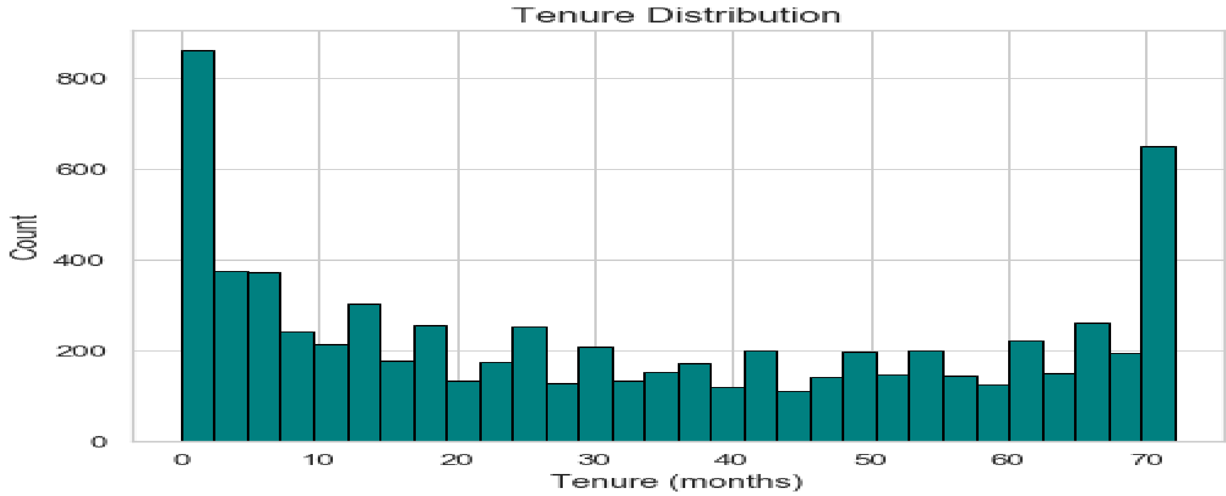


Fig 4. Tenure distribution based on months

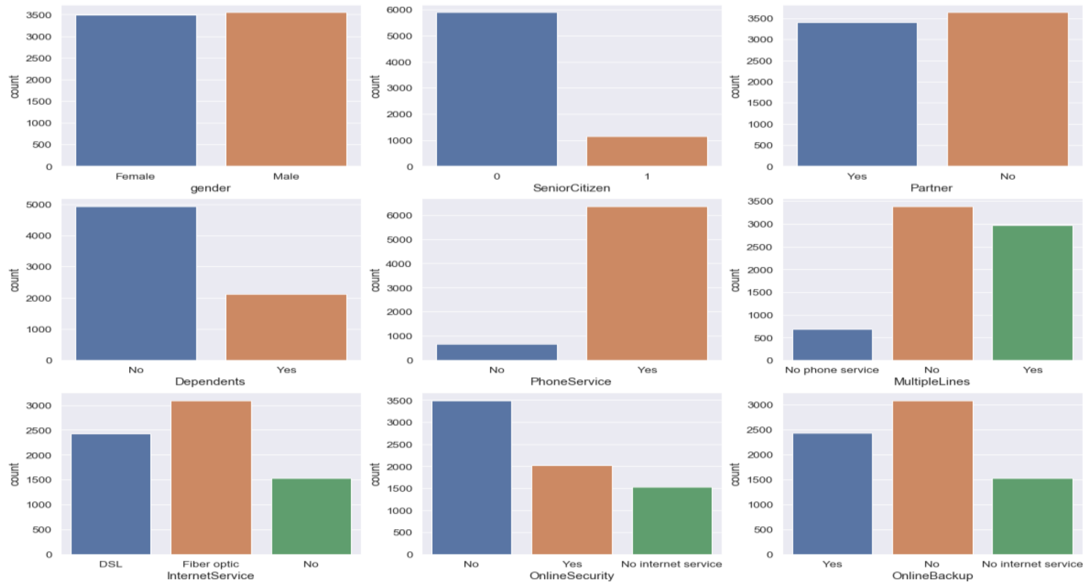


Fig 5. Visualize the distribution of categorical variables.

Fig. 6. Count the number of customers who left within the last month by gender.

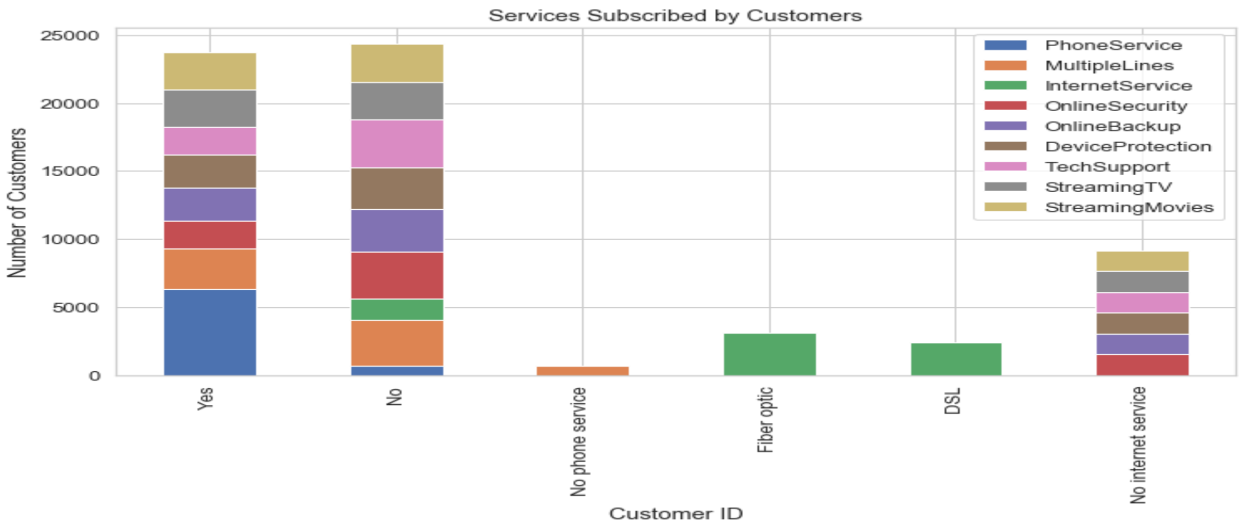


Fig. 7. Service counts as a stacked bar chart.

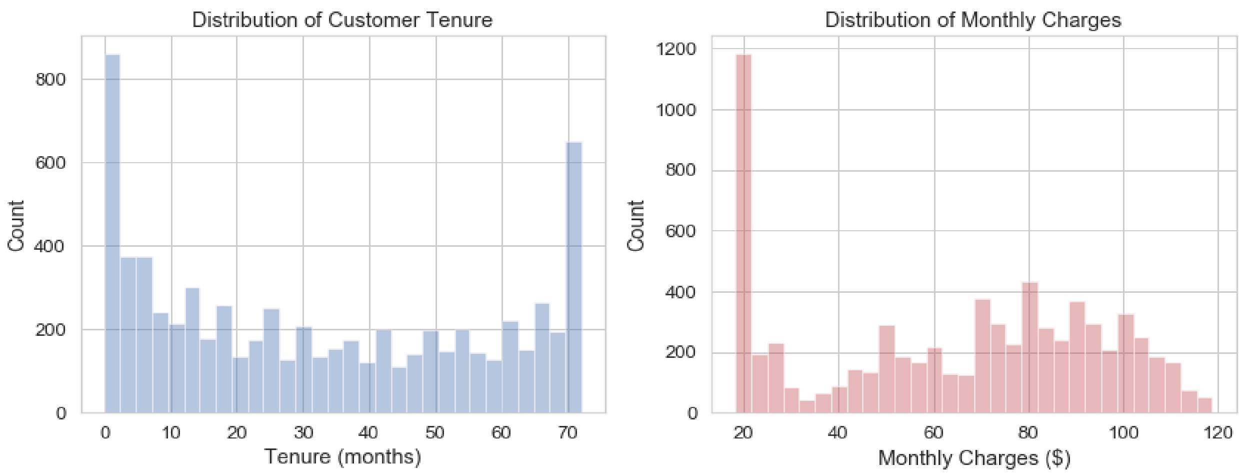


Fig. 8. Customer Tenure and monthly charges distribution

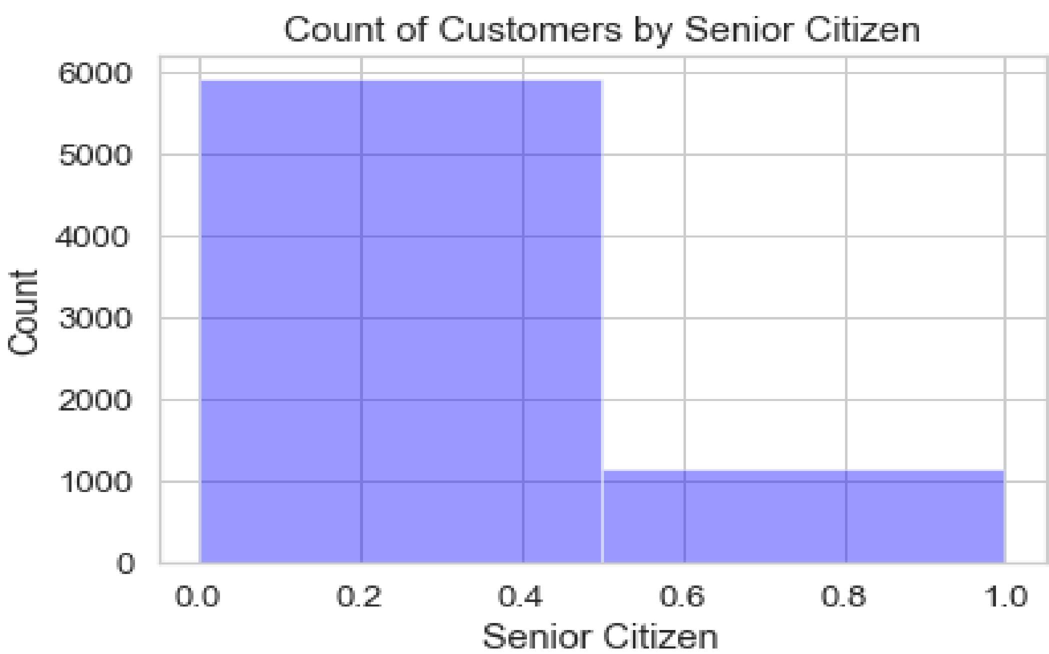


Fig. 9. Count of Customers by Senior Citizen

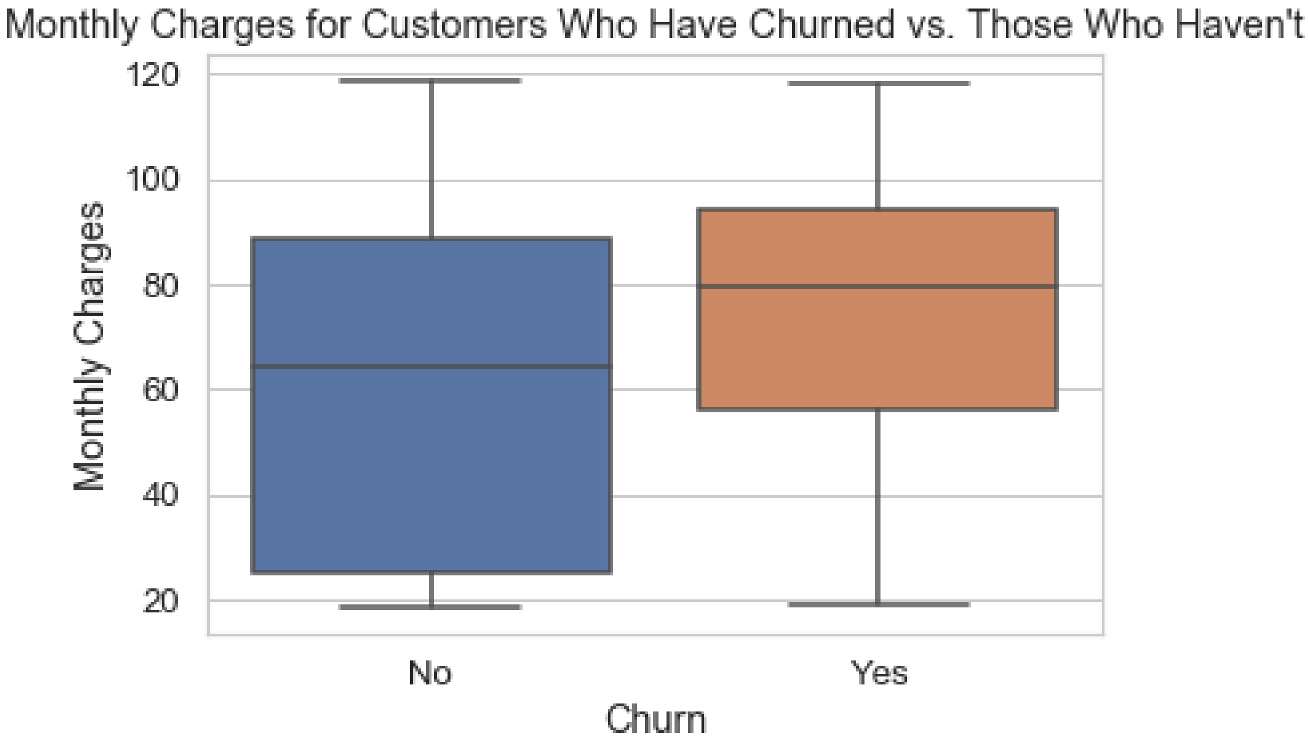


Fig. 10. Monthly Charges for Customers Who Have Churned vs. Those Who Haven't

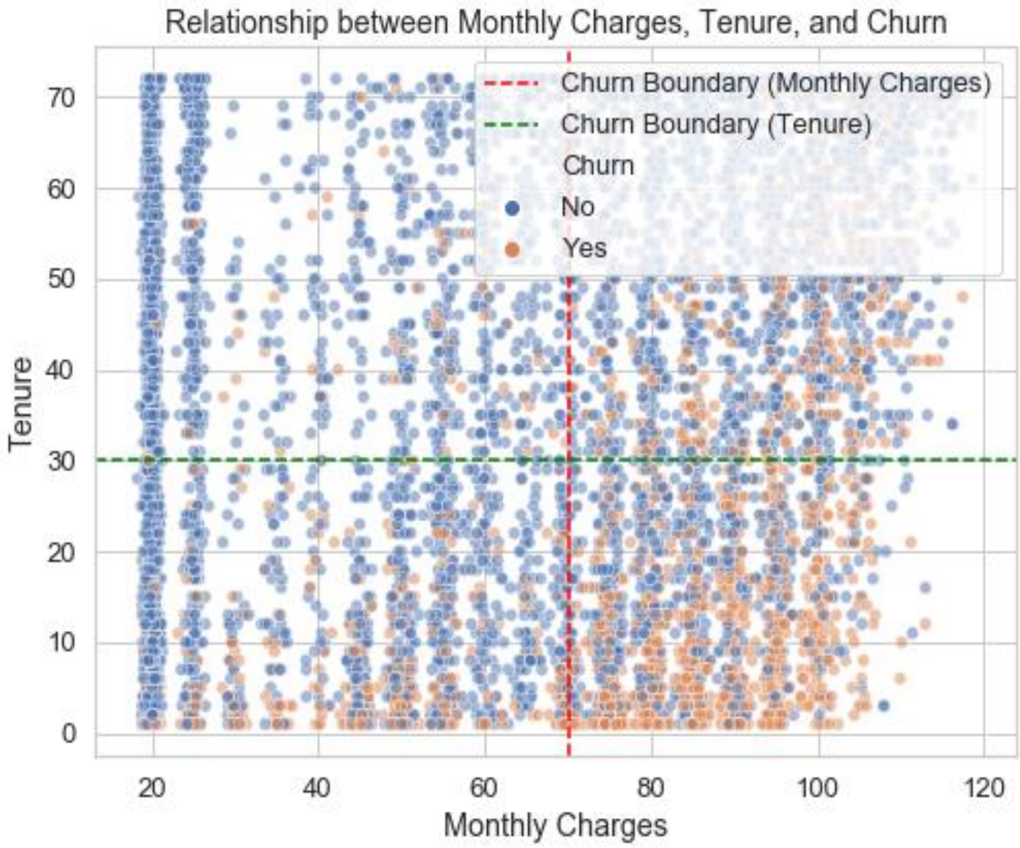


Fig. 11. Relationship between Monthly Charges, Tenure, and Churn

The study examined the factors influencing customer churn in a telecommunication company. It was observed that gender had no significant effect on churn as both male and female customers had almost equal churn rates. However, senior citizens were more likely to churn. Customers with partners and dependents had lower churn rates compared to those without. Fiber optic internet services had a higher churn rate than DSL. Customers without online security, online backup, and tech support services were more likely to leave. Monthly subscription customers had a higher churn rate than those with longer contract terms. Churn was also higher among customers who preferred paperless billing and electronic check payment methods. These findings can be used by the company to implement strategies aimed at reducing churn and retaining customers.

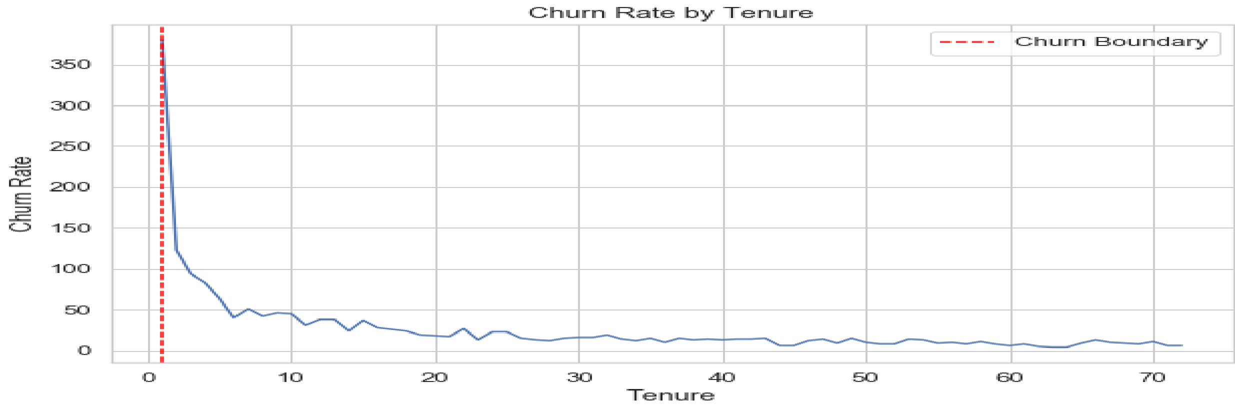
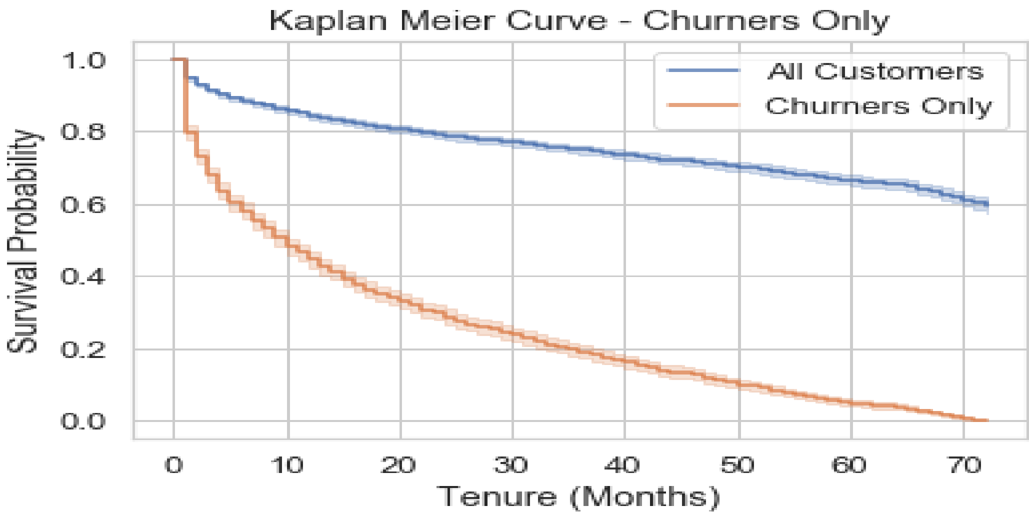


Fig. 12. Count of churned customers by tenure

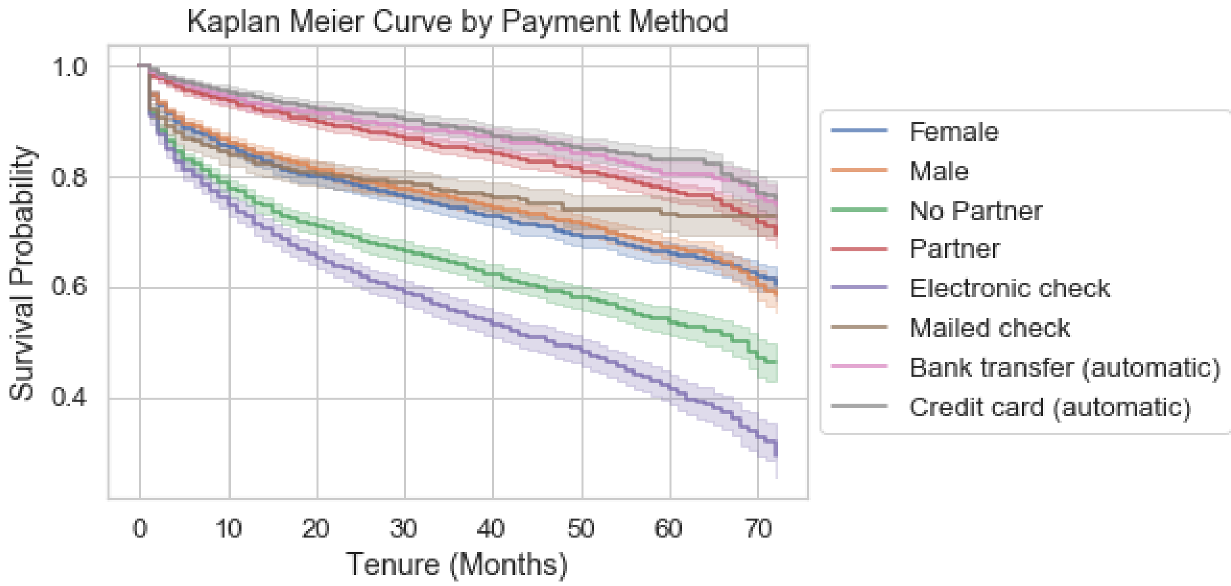
Survival Analysis

Based on the telco dataset, we conducted a survival analysis to understand the factors affecting customer churn. We used the Kaplan-Meier estimator to estimate the survival probability of customers and observed that the survival probability decreases significantly as the tenure of the customers increases. We further conducted stratified analysis by gender, partner, and payment method and found that gender and payment method do not have a significant impact on the survival probability of customers, while having a partner increases the survival probability. Our findings suggest that customer retention strategies should focus on improving the retention of customers with longer tenure and no partners.

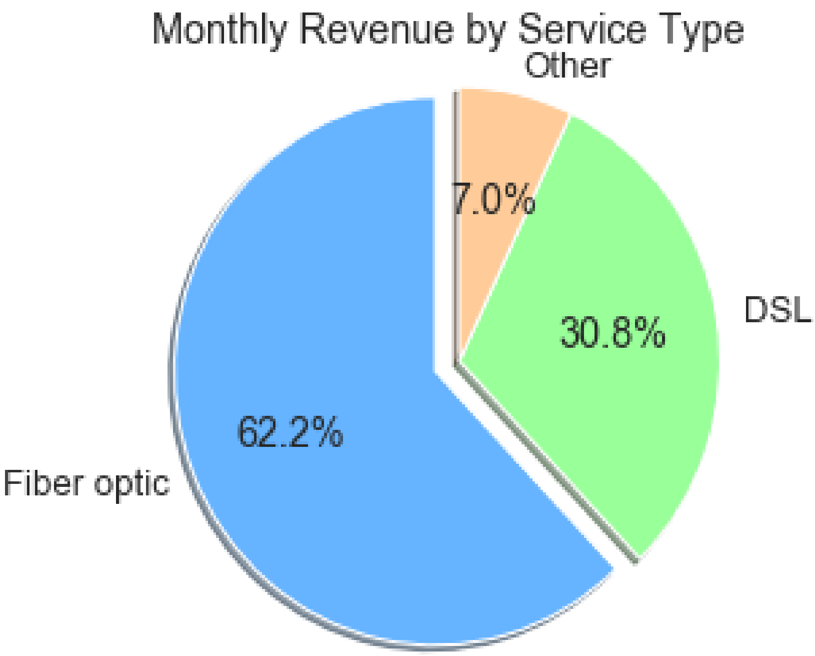


Fig, 13. Kaplan Meier curve for churners only

The following figure is visualizing Kaplan Meier curves for different customer groups based on gender, partnership status, and payment methods. The Kaplan Meier curves show the survival probability of customers over time, indicating the probability of them churning or staying with the company. This analysis can help the company identify which customer groups are more likely to churn and take appropriate measures to retain them.



Fig, 13. Survival Probability based on payment method



Fig, 13. Monthly Revenue based on Service type.

Based on our analysis, we found that customers with Month-to-Month Contracts did not contribute to any revenue loss due to churn. Additionally, Optical fiber was responsible for most of the monthly revenue, accounting for 62.2% (283.28k) of total revenue, while DSL accounted for 30.8% (140.34k). Interestingly, we also observed that the percentage of revenue lost due to churn was not available for customers with Month-to-Month Contracts.

Feature selection and Importance

The chi-square test is a statistical method used to determine whether there is a significant association between two categorical variables. In the context of feature selection, the chi-square test can be used to evaluate the significance of the association between each feature and the target variable. The results were plotted as a bar chart, where the features are sorted in descending order of importance score. The features with the highest importance scores, based on a chi-square test, were monthly revenue and total charges, followed by tenure and monthly charges. This suggests that these variables may have a strong association with the target variable (churn) in the dataset. Based on the chi-square test, Gender, Multiple lines, and Phone Services do not appear to be significantly associated with Churn, as their p-values are relatively high. Moreover, their survival curves do not show any notable differences. Additionally, it is recommended to drop columns that have a correlation coefficient greater than 0.9 and the Customer ID column, as they do not provide useful information and can potentially affect the model's performance.

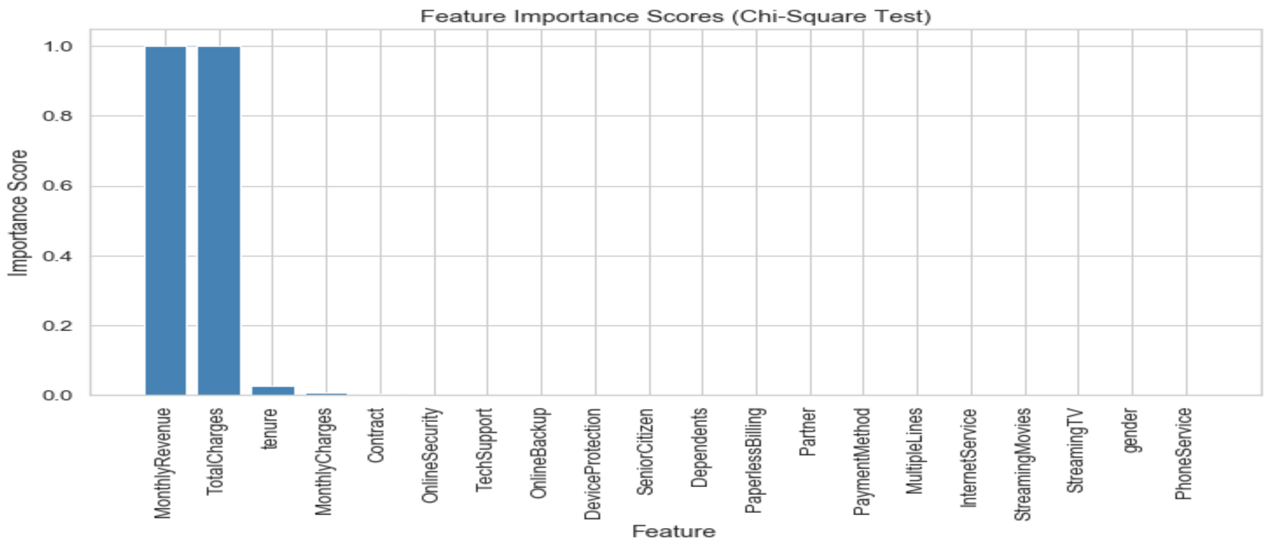


Fig. 14. Feature importance scores based on Chi-Square Test

Analysis of Variance (ANOVA): ANOVA is a statistical test used to compare the means of two or more groups. The purpose of this study was to investigate the potential predictors of customer churn in the telecommunications industry, specifically examining whether there were significant differences in tenure between customers who had churned and those who had not. Our ANOVA results indicated that there was a statistically significant difference in the tenure between these two groups, with a high F-value of 1007.51 and a very low p-value of 9.44e-207. This suggests that tenure may be a significant predictor of churn in the telecommunications industry.

ANOVA Result:

	sum_sq	df	F	PR(>F)
C(Churn)	1007.50943	1.00000	173.32900	0.00000
Residual	1007.50943	21094.00000	nan	nan

Wilcoxon Test: The Wilcoxon test, also known as the Mann-Whitney U test, is a non-parametric test used to compare two independent samples. In addition to the ANOVA test, we also used the Wilcoxon rank-sum test to investigate whether there were significant differences in monthly charges between customers who had churned and those who had not. Our Wilcoxon test results showed that there was a statistically significant difference in monthly charges between these two groups, with a negative statistic of 15.44 and an extremely low p-value of 8.47e-54. This suggests that customers who churn may be paying significantly different monthly charges than those who do not churn in the telecommunications industry.

Wilcoxon Result:

	meandiff	p-adj	lower	upper	reject
('No', 'Yes')	-15.44253	0.00000	-inf	inf	True

Based on our findings from both ANOVA and Wilcoxon tests, we conclude that both tenure and monthly charges are significant predictors of customer churn in the telecommunications industry. Customers who churn tend to have a shorter tenure and higher monthly charges compared to those who do not churn. These results have important implications for telecommunications companies, as they suggest that reducing monthly charges and improving customer retention efforts may be effective strategies for reducing customer churn. Further research is warranted to explore additional potential predictors of customer churn in the telecommunications industry.

Tukey HSD Post-hoc Test : The Tukey HSD post-hoc test is a statistical method used to determine whether there are significant differences between groups in a multiple comparison setting, such as when comparing the means of three or more groups. The Tukey HSD post-hoc test result indicates that there is a significant difference in the mean values of the Churn group for customers who did not churn (No) and customers who did churn (Yes). The reject column is True for this comparison, which means that the null hypothesis of equal means between these two groups is rejected. The mean difference between these two groups is -343.3617, which means that on average, customers who churned had lower values of the variable being analyzed (e.g., monthly charges, tenure, etc.) than those who did not churn.

Multiple Comparison of Means - Tukey HSD, FWER=0.05

group1	group2	meandiff	p-adj	lower	upper	reject
No	Yes	-343.3617	0.0	-394.4815	-292.2418	True

The inference from the Tukey HSD post-hoc test indicates that there is a significant difference in the mean values of tenure between customers who churned and those who did not. Specifically, customers who churned had a significantly lower mean tenure (about 343 months lower) than those who did not churn.

This suggests that tenure is an important factor in predicting customer churn, as customers who have been with the company for a longer period are less likely to churn. Companies could focus on retaining customers with lower tenure by offering incentives, better service, or other strategies to reduce the likelihood of churn.

Data Preprocessing

PCA (Principal Component Analysis): PCA (Principal Component Analysis) is a technique used for dimensionality reduction and feature extraction from high-dimensional datasets. It identifies the principal components of the data, which are new variables that capture most of the variance in the original dataset. These new variables are linear combinations of the original variables and are uncorrelated with each other.

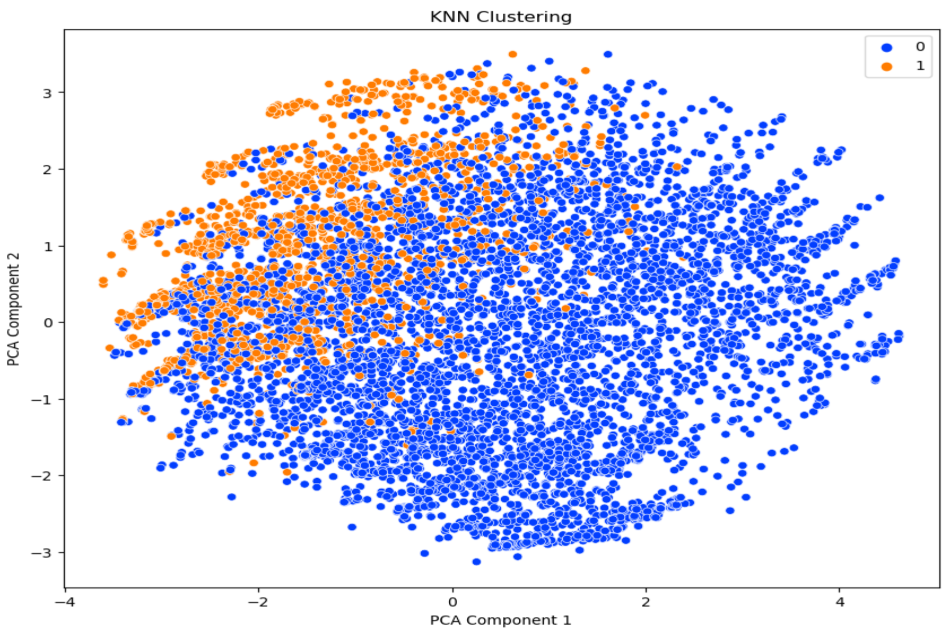


Fig. 15. Scatter plot of KNN clustering

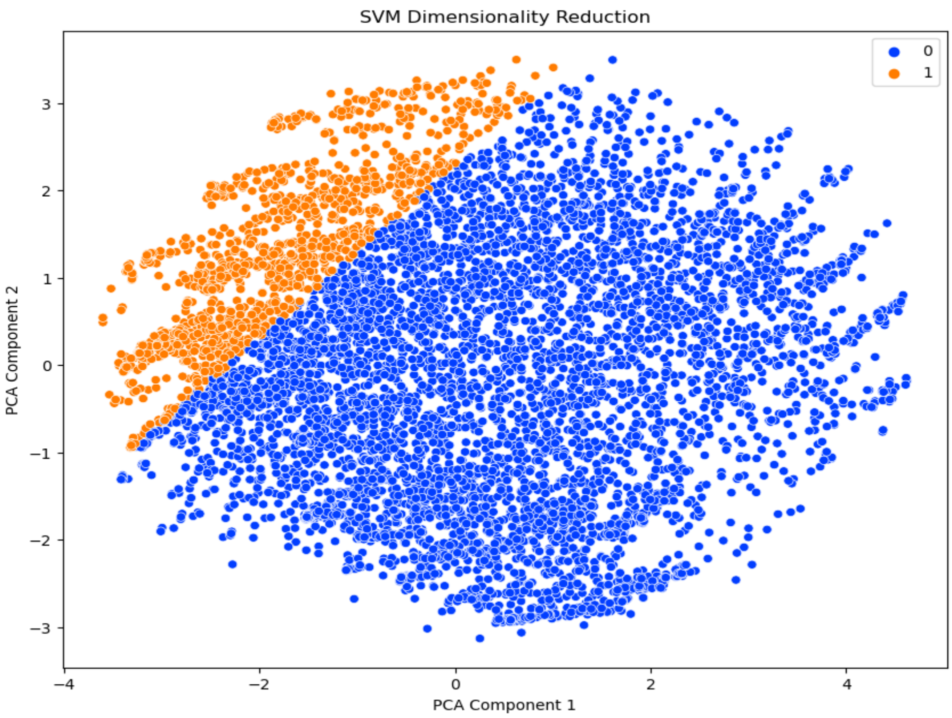


Fig. 16. Scatter plot of SVM dimensionality reduction

The scatter plots of KNN clustering and SVM dimensionality reduction provide a visual representation of how customers are clustered based on their features. The KNN clustering algorithm identifies groups of customers with similar features, while the SVM dimensionality reduction algorithm reduces the number of features and identifies the customers that are most likely to churn. The heatmap of the correlation matrix provides information about how the features are correlated with each other and how they impact customer churn.

Classification Methods

To improve the performance of the data, we performed classification using the following methods: Naive Bayes Classifier, Logistic Regression, Support Vector Machines (SVM), Gradient Boosting Classifier, XGBoost Classifier, LightGBM Classifier, CatBoost Classifier, and Neural Network Classifier. We evaluated the performance of each classification method using various metrics such as accuracy, precision, recall, and F1-score.

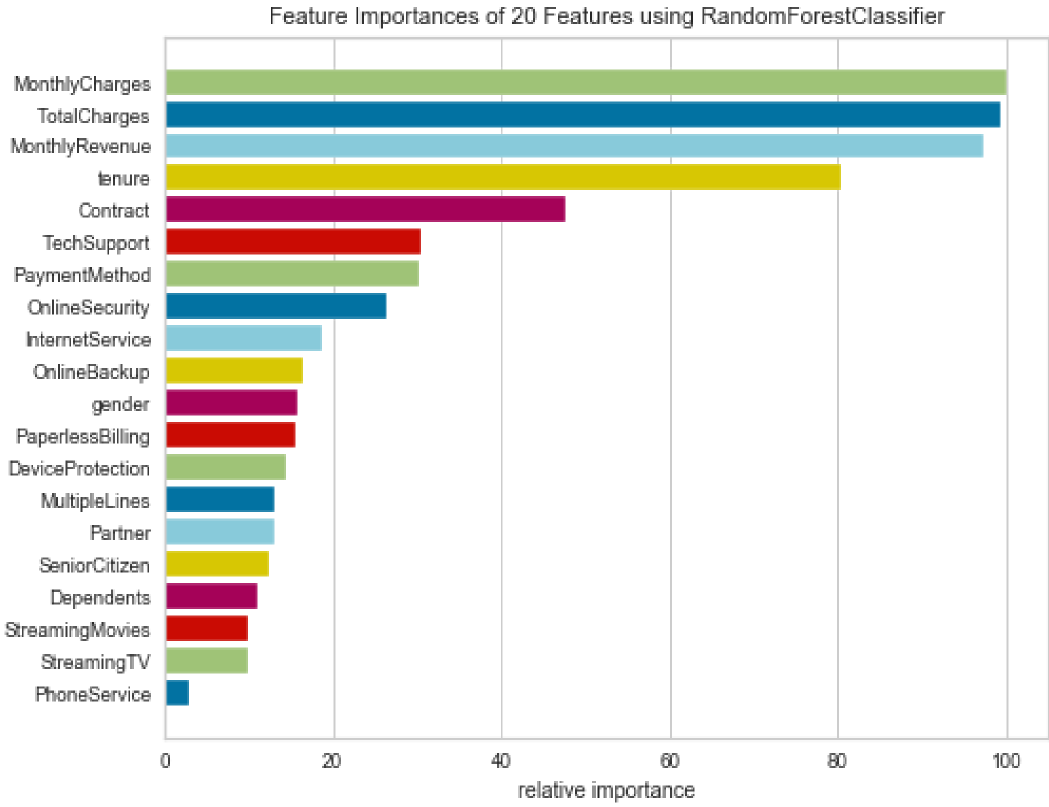


Fig. 17. Visualization of feature importance

Fig. 18. Model Loss of SVM Classifier

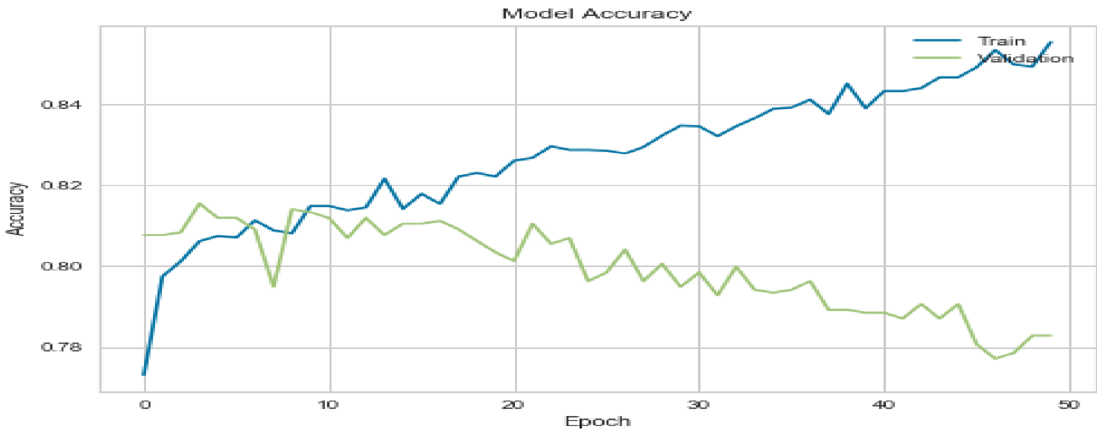


Fig. 19. Accuracy of SVM Classifier

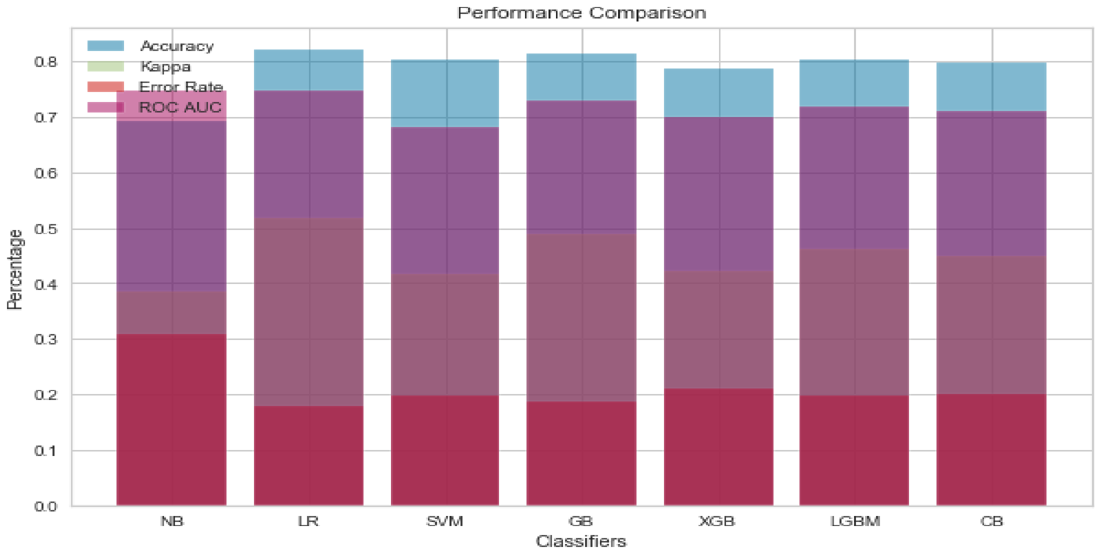


Fig. 19. Performance comparison of various Classifiers

Model Evaluation

The performance of the selected models was evaluated using various metrics such as accuracy, precision, recall, and F1 score. The models were also compared using receiver operating characteristic (ROC) curves and area under the curve (AUC) values. To ensure that the selected models were not overfitting or underfitting the data, they were also evaluated using cross-validation techniques such as k-fold cross-validation.

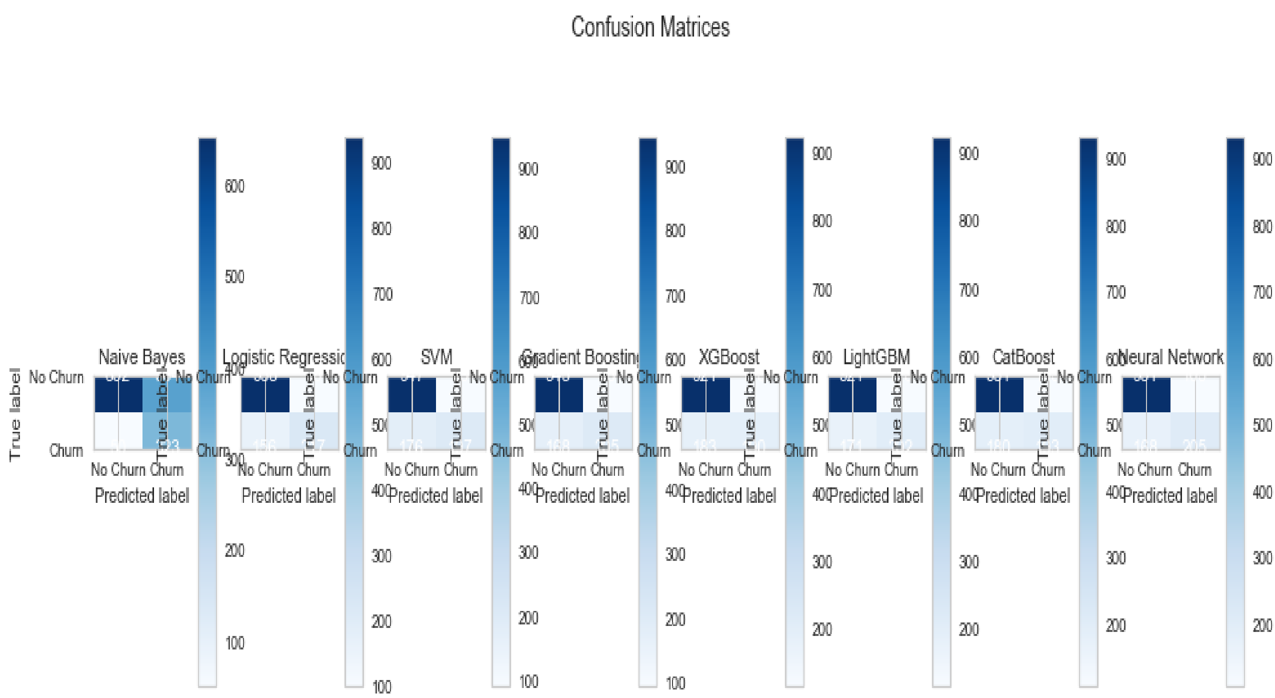


Fig. 20. Confusion matrices of all models

<table>
<tr><th>Model</th><th>Accuracy</th><th>Kappa</th><th>MSE</th><th>ROC AUC Score</th><th>Confusion Matrix</th></tr>
<tr><td>Naive Bayes</td><td>0.692</td><td>0.385</td><td>0.308</td><td>0.7476</td><td>652 | 384
--|---
50 | 323</td></tr>
<tr><td>Logistic Regression</td><td>0.8197</td><td>0.5127</td><td>0.1803</td><td>0.7436</td><td>938 | 98
--|---
156 | 217</td></tr>
<tr><td>SVM</td><td>0.8119</td><td>0.4779</td><td>0.1881</td><td>0.7211</td><td>947 | 89
--|---
176 | 197</td></tr>
<tr><td>Gradient Boosting</td><td>0.8148</td><td>0.4914</td><td>0.1852</td><td>0.7299</td><td>943 | 93
--|---
168 | 205</td></tr>
<tr><td>XGBoost</td><td>0.7885</td><td>0.4231</td><td>0.2115</td><td>0.6992</td><td>921 | 115
--|---
183 | 190</td></tr>
<tr><td>LightGBM</td><td>0.797</td><td>0.4523</td><td>0.203</td><td>0.7153</td><td>921 | 115
--|---
171 | 202</td></tr>
<tr><td>CatBoost</td><td>0.7977</td><td>0.4447</td><td>0.2023</td><td>0.708</td><td>931 | 105
--|---
180 | 193</td></tr>
<tr><td>Neural Network</td><td>0.8169</td><td>0.5005</td><td>0.1831</td><td>0.8546</td><td>941 | 95
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163 | 210</td></tr>
</table>

Fig. 21. Evaluation metrics

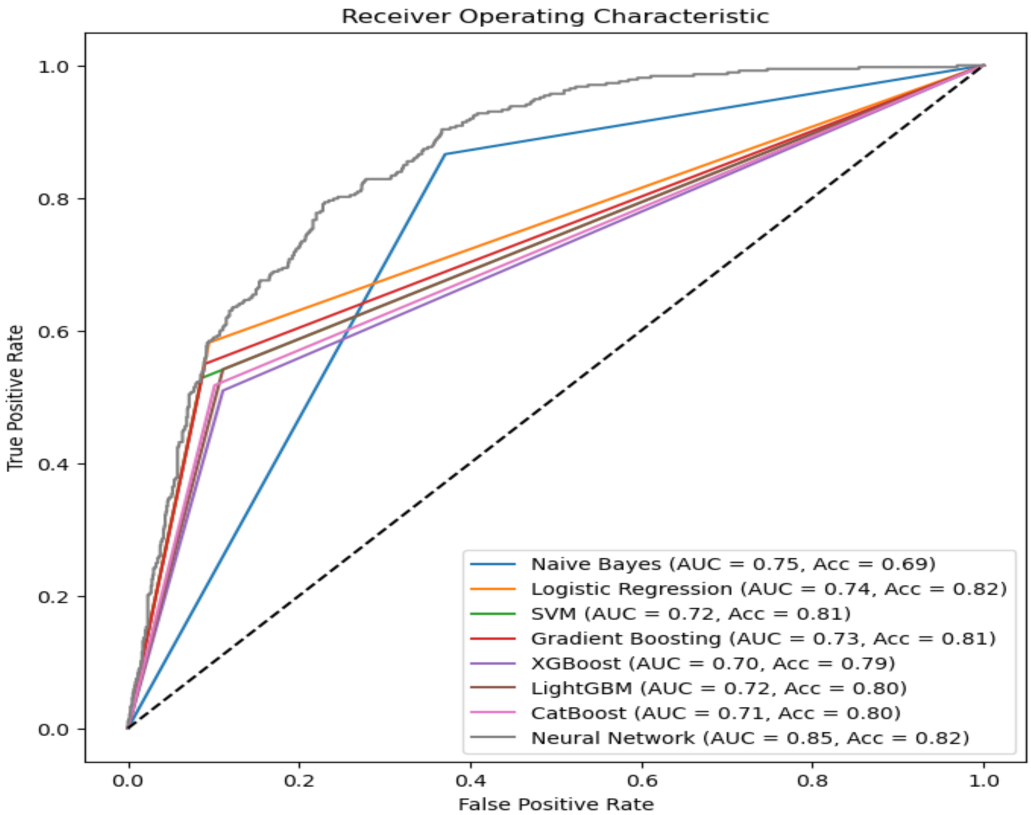

Fig.22 ROC Curves of all models

Performance Measures

In addition to model evaluation, hyperparameter tuning is also an important aspect of optimizing machine learning models. Hyperparameters are model settings that cannot be learned from data and must be set before training. By adjusting these hyperparameters, we can improve the performance of the model.

Grid search is a popular hyperparameter tuning technique that involves exhaustively searching over a predefined hyperparameter space to find the best combination of hyperparameters for a given model. This technique can be time-consuming, but it is often effective in improving model performance. Other techniques for hyperparameter tuning include random search, Bayesian optimization, and gradient-based optimization.

It is important to note that hyperparameter tuning should be performed using a separate validation set to avoid overfitting to the training data. After hyperparameter tuning, the final model should be evaluated on a held-out test set to estimate its true performance on unseen data. Overall, hyperparameter tuning is a critical step in the machine learning pipeline to achieve the best possible model performance.

Results and Discussion

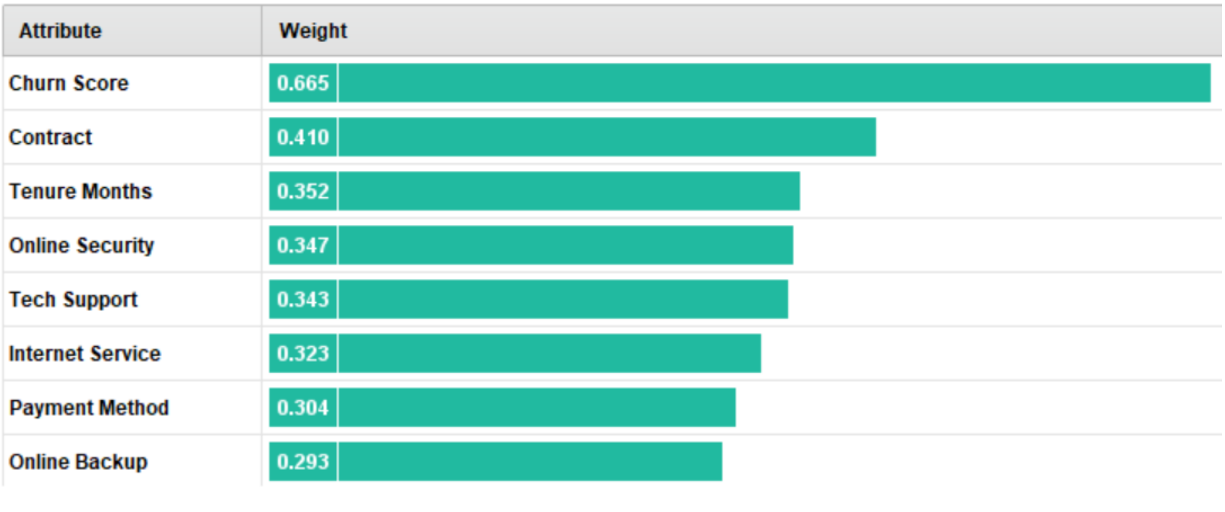

Fig. 23. Sample of Weights by Correlation Factors

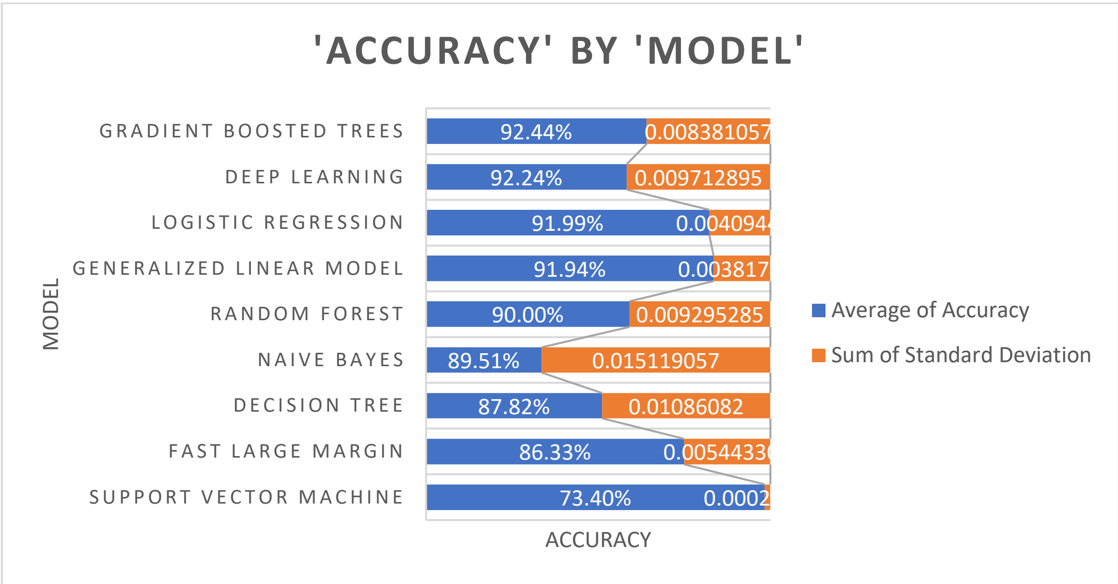

Fig. 24. Improved Accuracy after tuning the existing models.

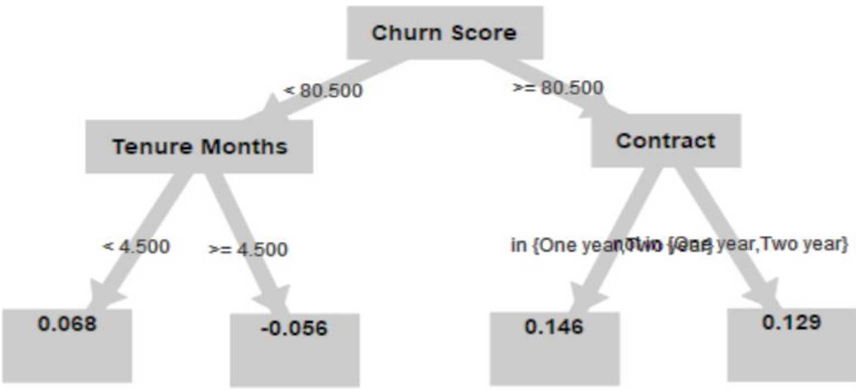

Fig. 25. Sample of Gradient Boost Tree

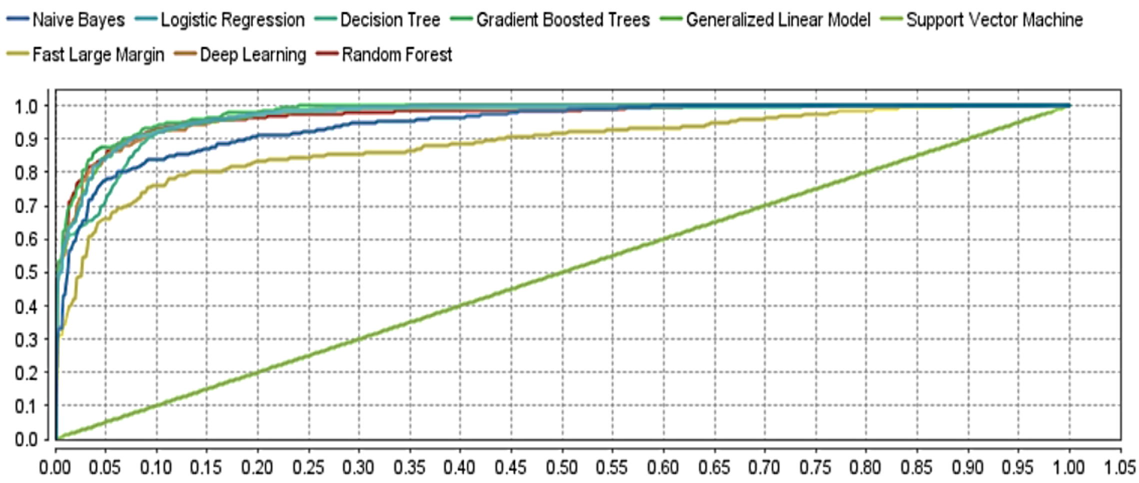

Fig. 26. ROC comparison of various models after tuning

Table I : ROC Comparison

Model	Accuracy	Error	AUC	Precision	Recall	F_Measure	Sensitivity	Specificity
Naive Bayes	0.8951	0.1049	0.9429	0.7971	0.8127	0.8045	0.8127	0.9248
Generalized Linear Model	0.9194	0.0806	0.9725	0.8691	0.8221	0.8441	0.8221	0.9546
Logistic Regression	0.9199	0.0801	0.9722	0.8664	0.8277	0.8457	0.8277	0.9533
Fast Large Margin	0.8633	0.1367	0.8854	0.8555	0.5843	0.6939	0.5843	0.9641
Deep Learning	0.9224	0.0776	0.9719	0.8568	0.8539	0.8541	0.8539	0.9472
Decision Tree	0.8782	0.1218	0.9644	0.8672	0.6424	0.7356	0.6424	0.9634
Random Forest	0.9000	0.1000	0.9697	0.7479	0.9419	0.8335	0.9419	0.8849
Gradient Boosted Trees	0.9244	0.0756	0.9781	0.8672	0.8465	0.8560	0.8465	0.9526
Support Vector Machine	0.7340	0.2660	0.5003		0.0000		0.0000	1.0000

4. Conclusion

In conclusion, our study employed various statistical, classification, and prediction models to analyze the factors affecting customer churn in the telecom industry. Based on our findings, we recommend that companies focus on predicting churn probabilities and engage with customers by offering better services and addressing complaints. It is also crucial to define the most valuable customers and allocate resources to retain them, while assigning the best people to deal with customers at risk of churn. Additionally, companies should highlight their competitive advantages and offer long-term contracts to promote customer loyalty. By implementing these strategies and continuously monitoring and adjusting them, telecom companies can reduce customer churn and improve their overall business performance.

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