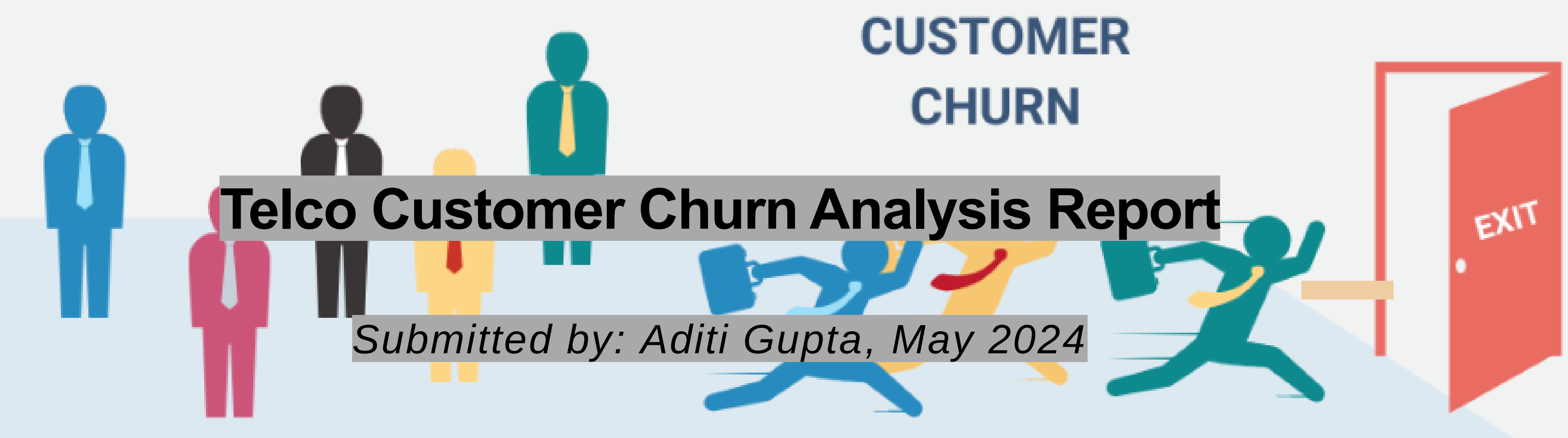

Telco Customer Churn Analysis Report

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INTRODUCTION

What is customer churn?

Customer churn is defined as when customers or subscribers discontinue doing business with a firm or service.

Customer churn is a critical challenge faced by the telecom industry. As customers switch from one service provider to another, telecom companies experience revenue loss and increased customer acquisition costs. To address this issue, we embarked on a project to develop machine learning models that can predict the likelihood of customer churn.

- Gather insights from the data to understand what is driving the high customer churn rate.
- Develop a Machine Learning model that can accurately predict the customers that are more likely to churn.
- Prescribe customized actions that could be taken to retain each of those customers.

DATASET

This dataset(link) if of JB Link a small size telecom company located in the state of California that provides Phone and Internet services to customers in more than a 1,000 cities and 1,600 zip codes.

Column Name	Description
Churn Value	1 = the customer left the company this quarter. 0 = the customer remained with the company
Customer ID	A unique ID that identifies each customer
Referred a Friend	Indicates if the customer has ever referred a friend or family member to this company
Number of Referrals	Indicates the number of referrals to date that the customer has made
Tenure in Months	Indicates the total amount of months that the customer has been with the company by the end of the quarter specified
Offer	Identifies the last marketing offer that the customer accepted, if applicable
Phone Service	Indicates if the customer subscribes to home phone service with the company
Avg Monthly Long-Distance Charges	Indicates the customer’s average long-distance charges, calculated to the end of the quarter
Multiple Lines	Indicates if the customer subscribes to multiple telephone lines with the company

Internet Service	Indicates if the customer subscribes to Internet service with the company
Internet Type	Indicates the type of Internet service the customer subscribes
Avg Monthly GB Download	Indicates the customer's average download volume in gigabytes, calculated to the end of the quarter
Online Security	Indicates if the customer subscribes to an additional online security service provided by the company
Online Backup	Indicates if the customer subscribes to an additional online backup service provided by the company
Device Protection Plan	Indicates if the customer subscribes to an additional device protection plan for their Internet equipment
Premium Tech Support	Indicates if the customer subscribes to an additional technical support plan from the company with reduced
Streaming TV	Indicates if the customer uses their Internet service to stream television programing from a third-party provider
Streaming Movies	Indicates if the customer uses their Internet service to stream movies from a third-party provider
Streaming Music	Indicates if the customer uses their Internet service to stream music from a third-party provider
Unlimited Data	Indicates if the customer has paid an additional monthly fee to have unlimited data downloads/uploads
Contract	Indicates the customer's current contract type
Paperless Billing	Indicates if the customer has chosen paperless billing
Payment Method	Indicates how the customer pays their bill
Monthly Charge	Indicates the customer's current total monthly charge for all their services from the company
Total Regular Charges	Indicates the customer's total regular charges, excluding additional charges
Total Refunds	Indicates the customer's total refunds
Total Extra Data Charges	Indicates the customer's total charges for extra data downloads above those specified in their plan
Total Long Distance Charges	Indicates the customer's total charges for long distance above those specified in their plan
Gender	The customer's gender

Age	The customer’s current age
Under 30	Indicates if the customer is under 30 years old
Senior Citizen	Indicates if the customer is 65 or older
Married	Indicates if the customer is married
Dependents	Indicates if the customer lives with any dependents: Yes, No. Dependents could be children, parents, grandparents, etc.
Number of Dependents	Indicates the number of dependents that live with the customer
City	The city of the customer’s primary residence
Zip Code	The zip code of the customer’s primary residence
Latitude	The latitude of the customer’s primary residence
Longitude	The longitude of the customer’s primary residence
Population	A current population estimate for the entire Zip Code area
CLTV	Customer Lifetime Value. A predicted CLTV is calculated using corporate formulas and existing data. The higher the value, the more valuable the customer
Churn Category	A high-level category for the customer’s reason for churning
Churn Reason	A customer’s specific reason for leaving the company
Total Customer Svc Requests	Number of times the customer contacted customer service in the past quarter
Product/Service Issues Reported	Number of times the customer reported an issue with a product or service in the past quarter
Customer Satisfaction	A customer’s overall satisfaction rating of the company from 1 (Very Unsatisfied) to 5 (Very Satisfied) collected on customer service requests

PROBLEM STATEMENT

JB link telco company is encountering a problem of a high 27% customer loss leading to a 12% drop in our customer numbers. And urgently need to forecast which customers are prone to churn and recommend tailored strategies to retain customers.

DATA WRANGLING

Data wrangling involved the following steps:

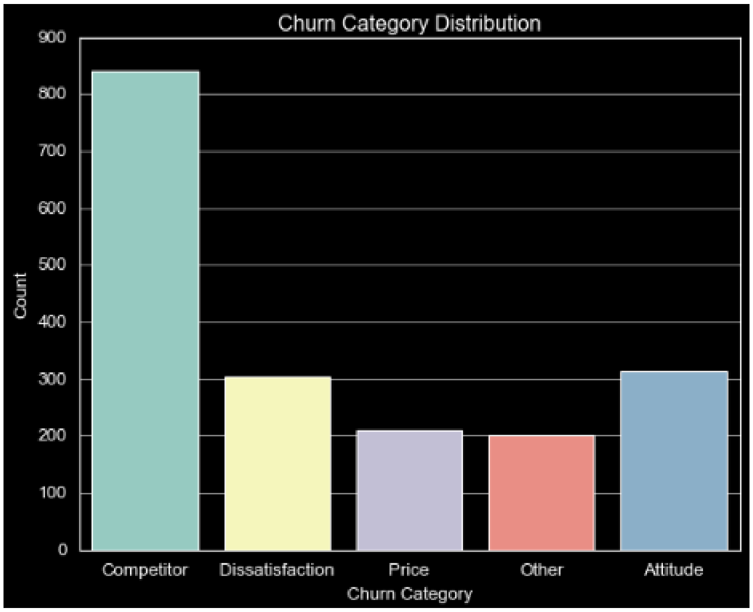
- **Importing the dataset**: Loaded the dataset into a pandas data frame.

- **Exploring data columns**: Used functions like head(), info(), and shape to understand the structure and size of the dataset.
- **Handling missing values**: Identified and visualized missing values, then decided on appropriate strategies for handling them.
- **Converting categorical data**: Converted categorical 'Yes'/'No' columns into binary (1/0) for easier analysis.

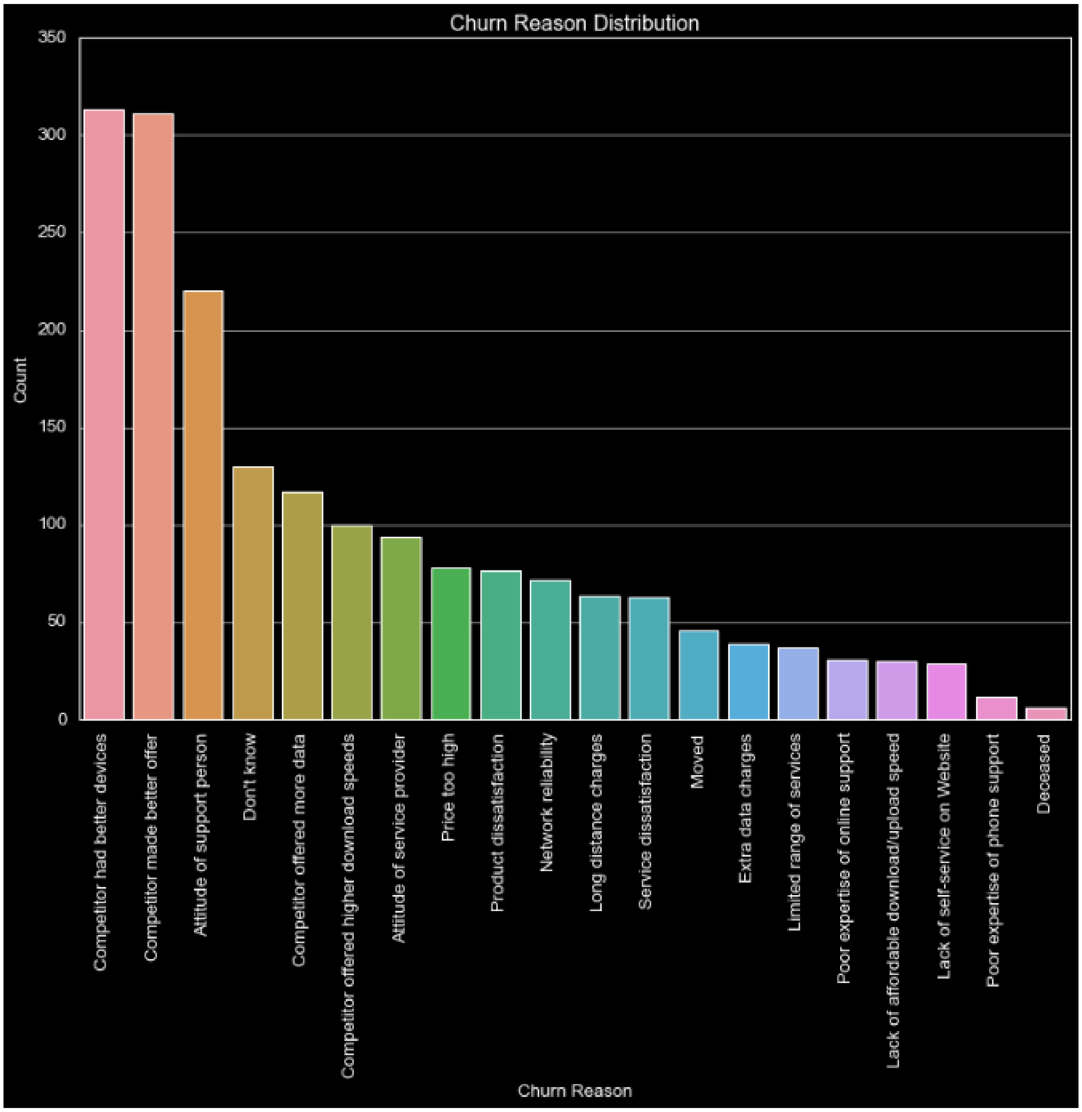
EXPLORATORY DATA ANALYSIS

Exploratory Data Analysis (EDA) helped in uncovering insights and patterns in the data:

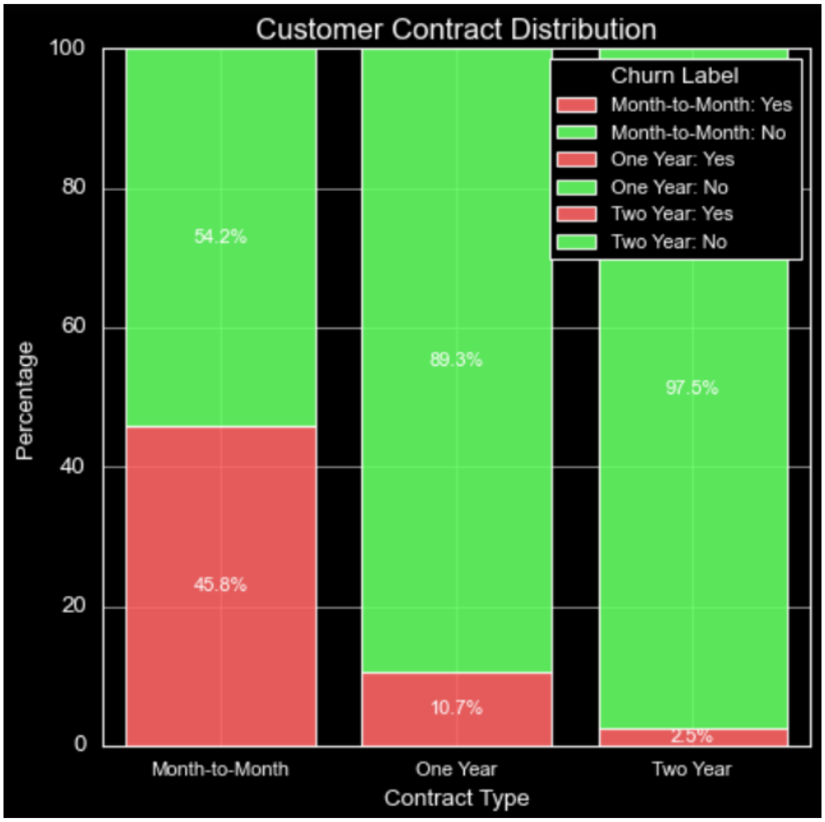
- **Customer Statistics**: Analyzed overall customer demographics and service usage.



- **Churn Reasons**: Examined the reasons why customers are churning, such as better service or pricing from competitors.

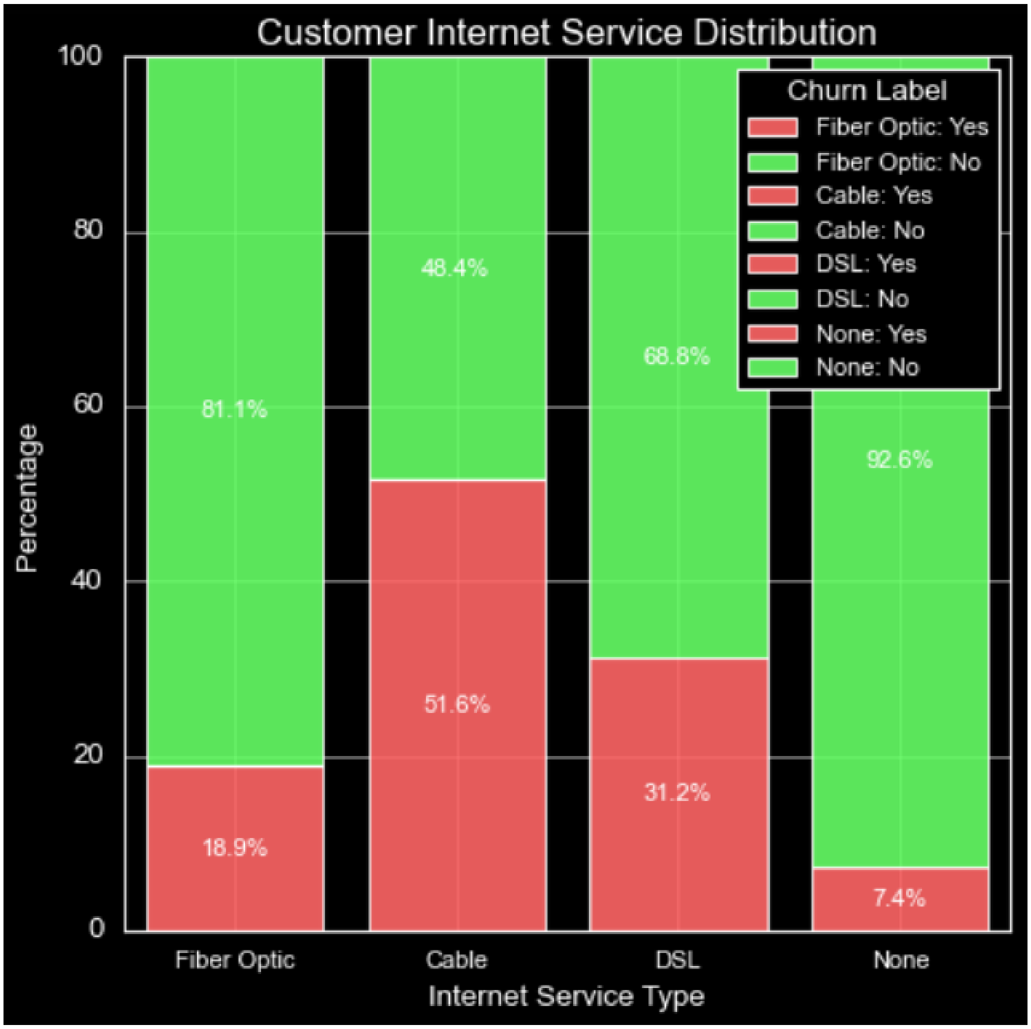


- **Key Insights**:
    - **Contract Type**: Customers with month-to-month contracts have a significantly higher churn rate. Approximately 54% of customers with month-to-month contracts churned, compared to only 11% with one-year contracts and 3% with two-year contracts.

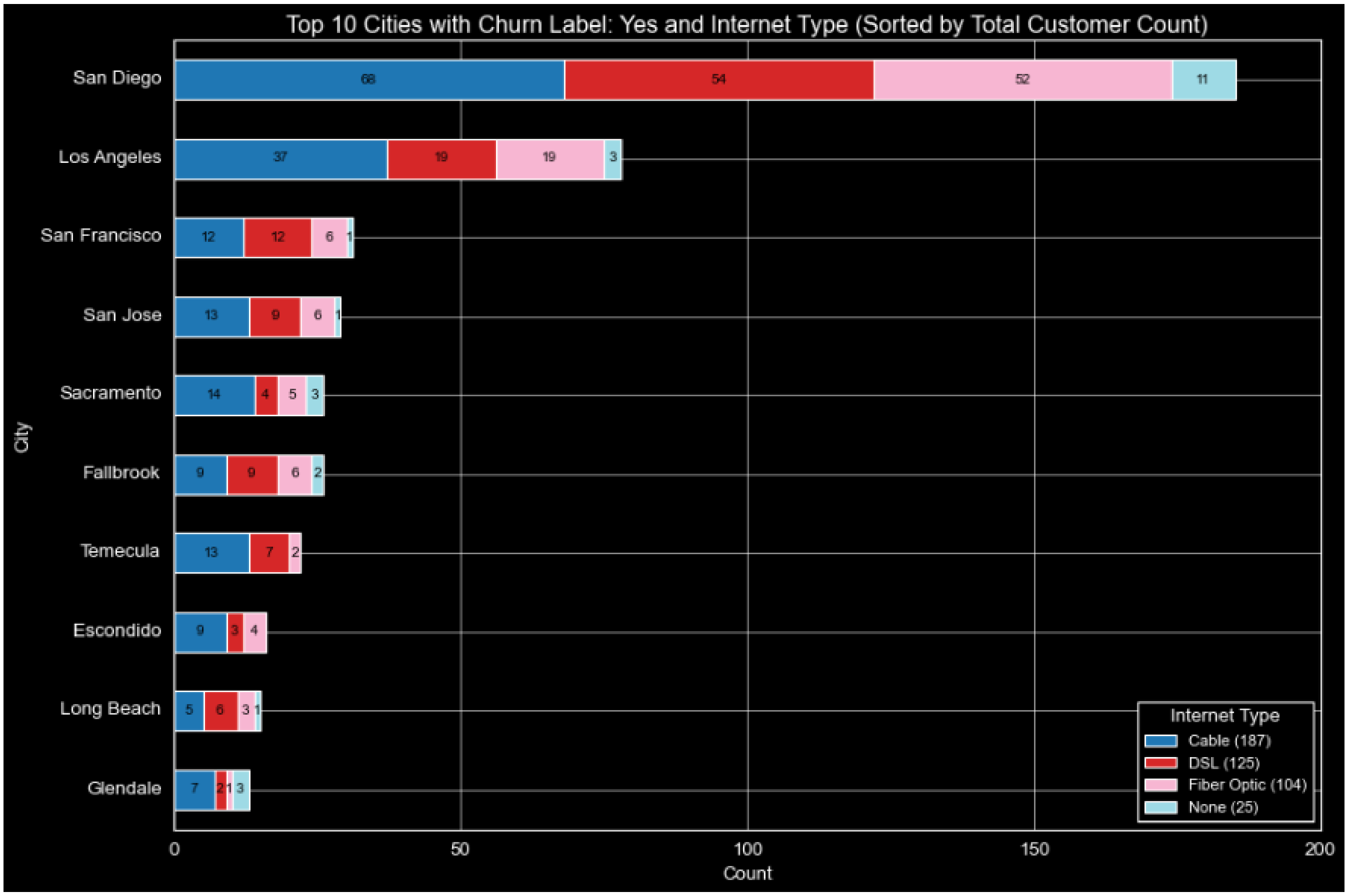


- **Customer Satisfaction**: Customers with satisfaction scores below 3 are more likely to churn. Visualization of customer satisfaction distribution highlighted that lower scores correlate with higher churn.

- **Internet Type**: Customers with cable or DSL services show higher churn rates compared to those with fiber optic services. This insight suggests that service quality differences impact customer retention.



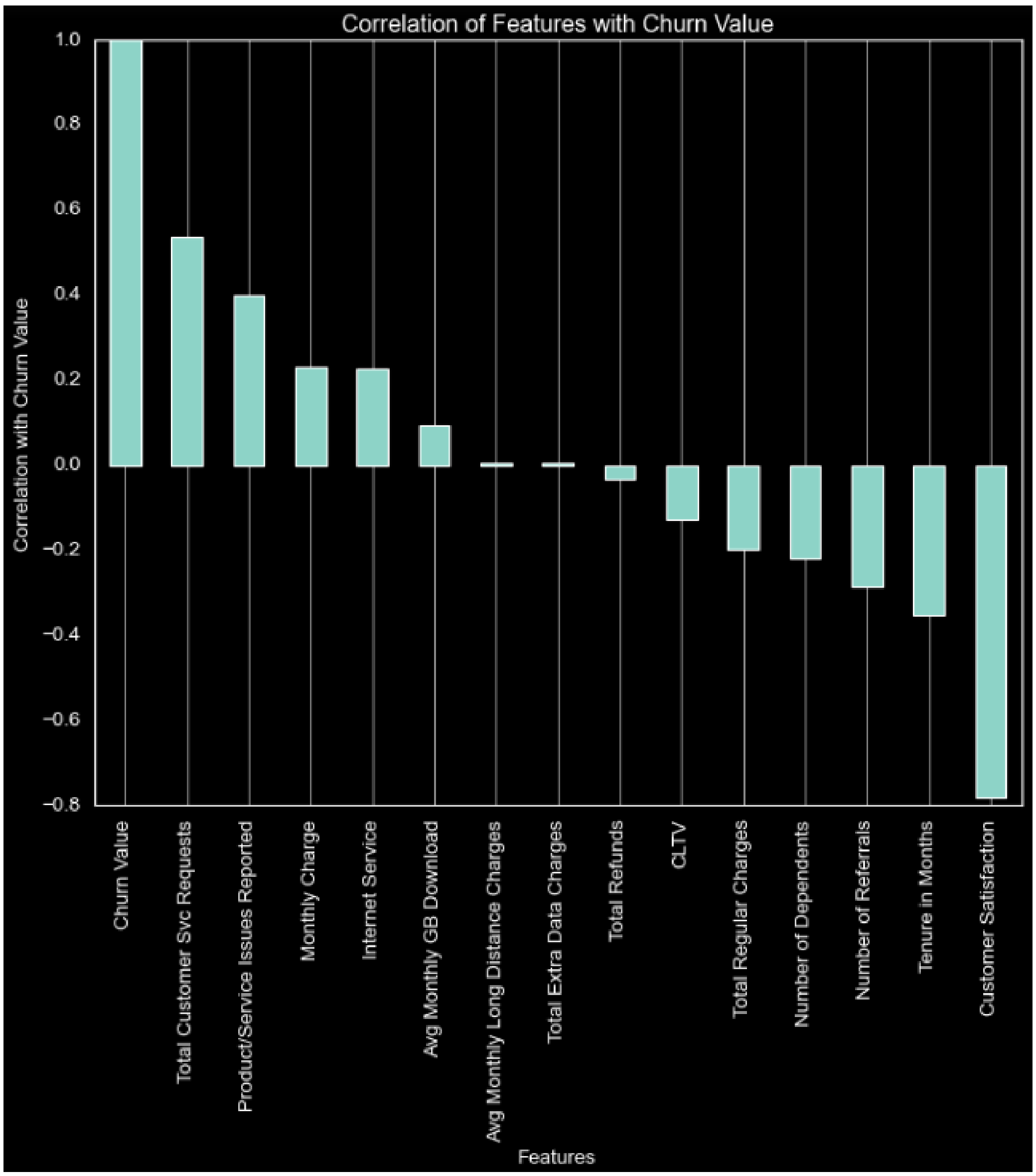
- **Geographic Analysis**: Los Angeles has the highest number of customers, but San Diego has the highest number of churned customers, with many citing better offers from competitors. This indicates a regional disparity in competitive pressure and customer retention.


Top 10 Cities with Churn Label: Yes and Internet Type (Sorted by Total Customer Count)
San Diego
Los Angeles
San Francisco
San Jose
Sacramento
Fallbrook
Temecula
Escondido
Long Beach
Glendale
City
Count
Internet Type
Cable (187)
DSL (125)
Fiber Optic (104)
None (25)

PREPROCESSING AND TRAINING

Pre-processing and training data development involved the following steps:

- **Feature Selection**: Removed unnecessary columns and retained features with significant correlation to churn. Created a correlation matrix to identify these features, setting a threshold of 0.2.



- **Data Transformation**: Converted categorical variables into numerical ones using one-hot encoding.
- **Data Splitting**: Split the data into training (80%) and testing (20%) sets to prepare for model training and evaluation.

MODELLING

The objective of this step was to build predictive models that accurately identify customers who are likely to churn. We evaluated three different machine learning models: Random Forest Classifier, Logistic Regression, and Histogram-based Gradient Boosting Classification Tree (HistGradientBoostingClassifier). Below are the detailed steps involved in the modeling process:

Model Selection

We chose the following models due to their distinct characteristics and potential effectiveness in classification tasks:

1. **Random Forest Classifier**:
   - An ensemble method that combines multiple decision trees to improve prediction accuracy and control over-fitting.
   - It can handle large datasets with higher dimensionality and is robust to missing values and outliers.
2. **Logistic Regression**:
   - A simple yet powerful model for binary classification problems.
   - Provides interpretable coefficients that can help in understanding the impact of each feature on the churn probability.
3. **HistGradientBoostingClassifier**:
   - A high-performance implementation of gradient boosting suitable for large datasets.
   - It builds trees iteratively, focusing on correcting errors made by previous trees, leading to improved accuracy.

Model Training

Each model was trained on the standardized training dataset. We used cross-validation to tune hyperparameters and prevent overfitting. Here are the steps for training each model:

1. **Data Preprocessing**:
   - Numerical features were standardized using StandardScaler.
   - Categorical features were converted to numerical values using one-hot encoding.
   - Data was split into training (80%) and testing (20%) sets.

MODEL EVALUATION

After training the models, we evaluated their performance using a set of standard metrics: Accuracy, F1 Score, Precision, Recall, and Confusion Matrix. These metrics provide insights into different aspects of model performance and help in selecting the best model.

Evaluation Metrics

1. **Accuracy**:

    - The proportion of correctly predicted instances out of the total instances.
2. **F1 Score**:
    - The harmonic mean of precision and recall. It provides a balance between these two metrics, especially useful for imbalanced classes.
3. **Precision**:
    - The proportion of true positive predictions out of all positive predictions. High precision indicates a low false positive rate.
4. **Recall**:
    - The proportion of true positive predictions out of all actual positives. High recall indicates a low false negative rate.
5. **Confusion Matrix**:
    - A table that describes the performance of a classification model by comparing predicted and actual values.

Model Performance

Here are the results for each model:

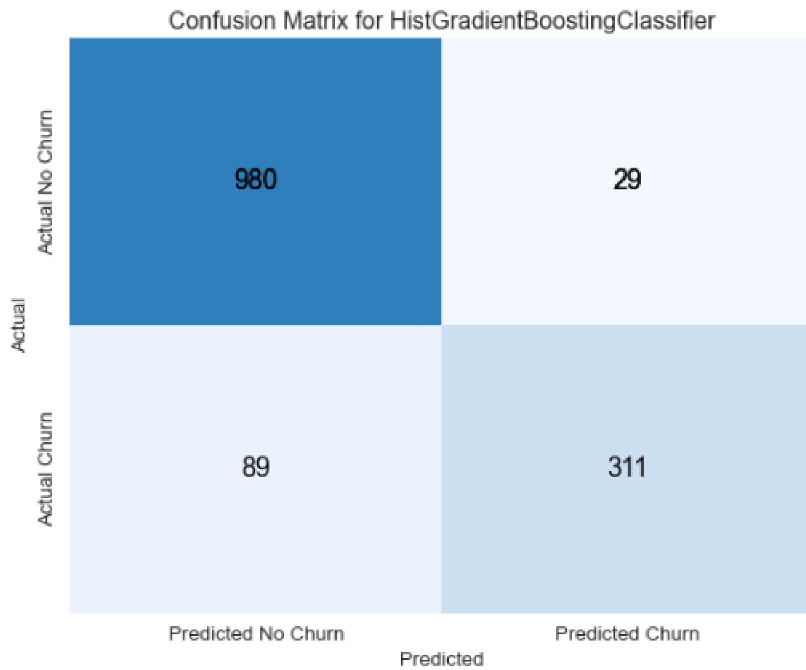
Model	**Accuracy**	**F1 Score**	**Precision**	**Recall**	**Confusion Matrix**
Random Forest Classifier	89.85%	80.59%	88.13%	74.25%	[[969, 40], [103, 297]]
Logistic Regression	88.64%	77.65%	87.97%	69.50%	[[971, 38], [122, 278]]
HistGradientBoostingClassifier	91.62%	84.05%	91.47%	77.75%	[[980, 29], [89, 311]]

Best Model Selection

The HistGradientBoostingClassifier outperformed the other models across all metrics. It achieved the highest accuracy (91.62%), F1 score (84.05%), precision (91.47%), and recall (77.75%). Therefore, we selected the HistGradientBoostingClassifier as our final model.

Confusion Matrix Analysis

The confusion matrix for the HistGradientBoostingClassifier was as follows:



- **True Positives (TP)**: 311
- **True Negatives (TN)**: 980
- **False Positives (FP)**: 89
- **False Negatives (FN)**: 29

Key Findings:

- **High True Positives and True Negatives**:
  - The model correctly identified a large number of both churned and non-churned customers.
- **Low False Negatives**:
  - Only 29 false negatives, indicating that the model missed few actual churn cases.
- **Moderate False Positives**:
  - 89 false positives, which is manageable but indicates some over-prediction of churn.

5.5 Implications

- **True Positives**:
  - Correctly identifying customers who are likely to churn allows the company to take proactive measures to retain these customers.
- **True Negatives**:
  - Correctly identifying customers who are not likely to churn avoids unnecessary retention efforts.
- **False Positives**:
  - These represent customers incorrectly predicted to churn, potentially leading to unnecessary retention offers.
- **False Negatives**:
  - These represent churn cases missed by the model, where no retention action would be taken.

CONCLUSION

The HistGradientBoostingClassifier demonstrated the best performance, making it the recommended model for predicting customer churn. This model's high accuracy, precision, and recall ensure it can effectively identify customers at risk of churning, allowing JB Link Telecom to implement targeted retention strategies.

RECOMMENDATIONS

1. **Customer Retention Strategies**:
    - **Customer Retention Programs**: Focus on customers with month-to-month contracts and low satisfaction scores by offering them incentives or improved service plans.
    - **Service Improvement**: Address issues with cable and DSL services to reduce churn in these segments. Invest in upgrading infrastructure to match the performance of fiber optic services.
    - **Targeted Offers**: Use the predictive model to identify customers at high risk of churning and provide them with personalized offers or loyalty programs to retain them.
    - **Customer Support Enhancement**: Improve customer service response times and effectiveness to enhance overall customer satisfaction and reduce churn related to service issues.
2. **Ongoing Model Maintenance**:
    - Regularly retrain the model with new data to ensure its predictions remain accurate.
    - Monitor model performance and adjust hyperparameters as needed.

FUTURE SCOPE OF WORK

To further improve the churn prediction model and customer retention strategies, consider the following future work:

- **Model Tuning**: Perform hyperparameter tuning on the HistGradientBoostingClassifier to further improve its performance, especially focusing on increasing recall if the cost of false negatives is high.
- **Feature Engineering**: Explore additional feature engineering techniques to create new features that might capture underlying patterns not evident in the current dataset.
- **Data Enrichment**: Integrate additional data sources such as social media interactions, customer feedback, and competitive market data to provide a more comprehensive view of customer behavior and churn drivers.
- **Real-Time Prediction**: Implement the churn prediction model in a real-time environment to provide immediate insights and allow for timely interventions.

- **A/B Testing**: Conduct A/B testing on retention strategies to evaluate their effectiveness and refine approaches based on empirical results.

By implementing these strategies and continuing to enhance the predictive model, JB Link can effectively reduce customer churn, retain more customers, and ultimately improve its revenue and customer satisfaction.