

Dynamic Churn Prediction using Machine Learning Algorithms - Predict your customer through customer behaviour

Viraj thorat¹, Sonali sanap², Prof. Satish cholke³

Sir Vishvesvarayya Institute of Technology^{1,2}

Collage- Sir Vishvesvarayya Institute Of Technology Nashik³

Abstract: In today's business landscape, customers are increasingly drawn to the quality of service (QoS) offered by organizations. However, the current era is marked by intense competition in delivering technologically advanced QoS to customers. Nevertheless, implementing efficient customer relationship management (CRM) systems can provide several advantages for organizations. These include acquiring more customers, fostering strong customer relationships, and enhancing customer retention, ultimately leading to increased profitability for the business. Additionally, integrating machine learning models such as support vector machine algorithms can further enhance customer retention strategies.

Keywords—customer relationship management, customer retention, machine learning, support vector algorithm

I. INTRODUCTION

The satisfaction and loyalty of customers significantly impact an organization's profitability and revenue. To ensure customer satisfaction, it is crucial for managers to implement an efficient customer relationship management (CRM) system. This system facilitates the selection of target customers and enables effective relationship management with them. Furthermore, implementing a CRM system helps organizations identify key customer segments and understand their behavior, providing valuable insights for developing effective retention strategies. In particular, customer loyalty plays a vital role in reducing customer churn, or the rate at which customers stop using a company's products or services. To enhance customer retention, machine learning algorithms such as the support vector machine (SVM) algorithm can be employed. SVM algorithms offer value in preventing customer churn by analyzing customer data and identifying patterns that may indicate potential churn. This report will primarily focus on customer retention strategies, highlighting the utilization of support vector machine learning to increase customer loyalty and retention. By leveraging the insights provided by SVM algorithms, organizations can develop targeted approaches to retain customers and foster long-term relationships. The objective is to understand how the implementation of SVM algorithms in CRM systems can contribute to improving customer retention, thereby driving growth and profitability for the organization.

II. BACKGROUND

Customer churn can occur in two ways: voluntary churn, where customers willingly terminate their relationship with a particular seller, and involuntary churn, where customers are forced to end their business association with an entity. Involuntary churn typically happens when customers fail to comply with the established rules governing commerce within a specific setting. Examples of such non-compliance may include engaging in illegal practices like theft or refusing to make timely payments [2]. On the other hand, voluntary churn is driven by factors such as customer dissatisfaction or the organization's failure to maintain a competitive advantage. Evaluating churn practices is crucial for any organization that interacts with diverse customer type. s.

III. CAUSES OF CHURNING.

The impact of customer churn on an organization can negatively affect its revenue for a given product or service. When customers who have previously churned share their negative experiences, it can deter potential customers from engaging in transactions with the company. Often, customer expectations may not align with the actual product or service they receive, leading them to seek alternatives from different providers.

In the case of machinery-producing companies, convincing buyers to choose a particular machine becomes challenging if they test it and find that it underperforms. Customers are likely to switch to other sellers offering better-performing alternatives. Effective consumer management strategies become crucial in such instances, prompting organizations to improve the quality of their production and enhance their brand portfolio [4]. Price is a significant factor driving customers away from a product. Customers feel the burden of acquiring expensive commodities and services, especially when cheaper alternatives that can fulfill their needs exist in the market. Price variations among products can undermine an organization's ability to retain customers compared to their competitors.

Customers often compare the pricing of a particular company's offerings to that of similar companies to assess the value of the product. If the pricing model is perceived as flawed by consumers, potential buyers are likely to reject the company's products.

Customer satisfaction is a critical determinant of whether a buyer will continue doing business with a particular company or seek alternatives. When customers' expectations are met or exceeded, they are more likely to stick with entities that provide excellent customer care services. Establishing a habit of purchasing from a specific seller can lead to customer loyalty, and it is the responsibility of the organization to maintain customer satisfaction to retain their loyalty.

IV. CONCEPTUAL FRAMEWORK.

Elements of the marketing mix theory provide valuable insights into why customers choose to disengage from a particular business. Product features, particularly quality and price, significantly influence customer perceptions of a company. For example, a study conducted in the Australian telecommunications industry revealed that network quality played a crucial role in customers' decisions to avoid using local networks [1]. The poor quality of the network adversely affected a large number of users, particularly those who relied on calling and internet browsing services. Pricing and promotions also have a significant impact on consumer behavior in any market. When a company offers favorable prices to its customers, it can increase and maintain customer loyalty.

The expectation and confirmation theory further explain consumer behavior. A customer's expectations play a crucial role in determining whether they will purchase a particular product. It is the responsibility of a company's marketing team to ensure that their prices meet customer expectations [3].

When customers receive the expected level of service and confirm that it meets their standards, it strengthens their bond with the company. Conversely, if customers feel that the service falls below their expectations, such as in the case of the Australian telecommunications industry, it can lead to dissatisfaction and disengagement.

V. CHURN PREDECTION

Analyzing the rate at which customers leave an organization involves conducting churn analysis. In the telecommunications industry, churn refers to the number of customers who have discontinued their subscriptions within a specific time period [4]. A typical churn rate measures the movement of customers in and out of a company during a given timeframe. Specifically in the telecommunications industry, churn refers to customers switching from one company to another [5]. Currently, there is a significant increase in the number of churn customers as the industry strives to retain more profitable customers. Figure 2 illustrates the algorithm used to train the data set and model.

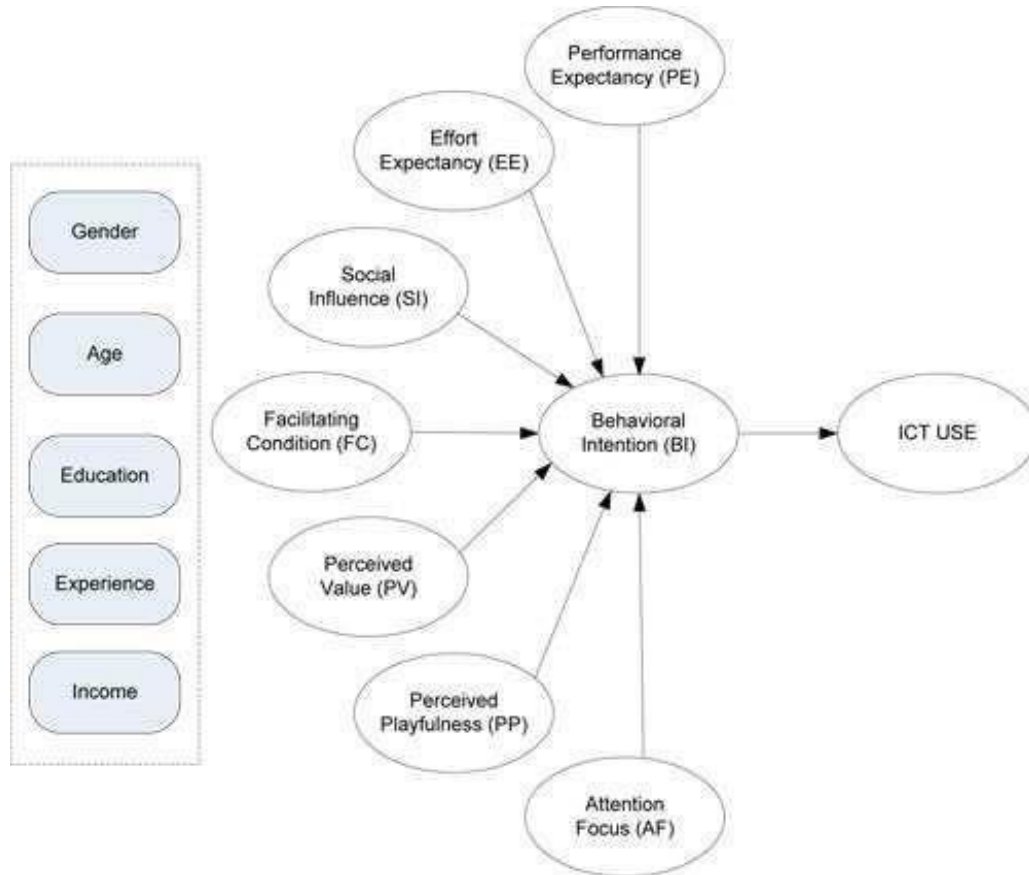


Fig .1. Conceptual model of consumer behavior.

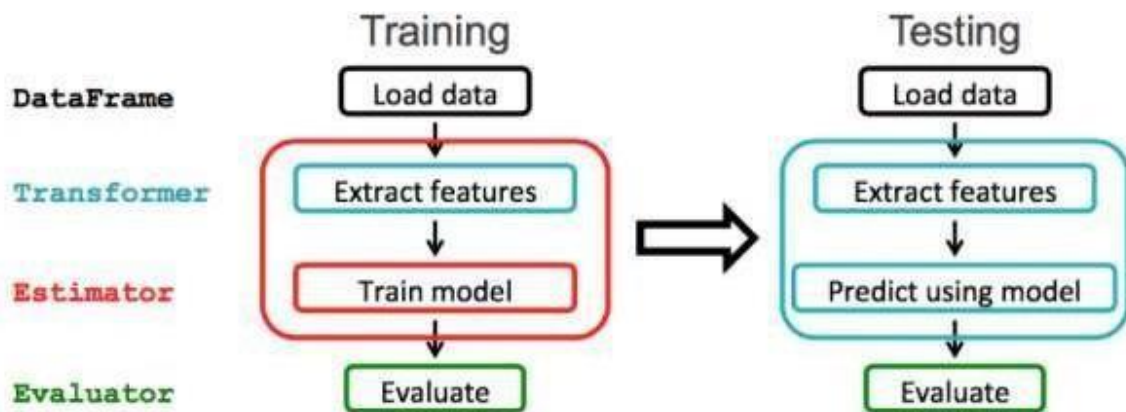


Fig. 2. An algorithmic flowchart.

Churn can be classified into two types. Involuntary churn occurs when customers are removed by the industry itself due to nonpayment of bills, fraudulent activities, or other similar reasons. On the other hand, voluntary churn happens when customers intentionally decide to change or leave the organization [6]. In the telecom industry, the continuous growth of service providers is a key factor contributing to an increase in churn customers for companies. However, understanding customer demands and cultivating customer loyalty can help reduce churn rates. Identifying the strongholds and weak points of a company to its trading behavior [5]. Also, in the broader context, it is important to note that data analysis is an ongoing process, as consumer behavior can evolve over time. Regularly analyzing and monitoring data allows businesses to stay updated on market trends and adapt their strategies accordingly. By utilizing data analysis tools effectively, organizations can optimize their marketing efforts, improve customer engagement, and drive business growth.

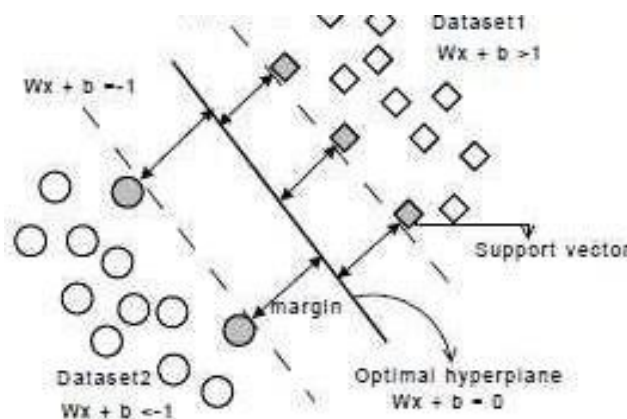
VI. PREDICTION OF THE CHURNING THROUGH A MACHINE ALGORITHM.

Data analysis is a valuable tool for understanding instances of customer dissatisfaction in business. In particular, e-commerce platforms can effectively utilize consumer databases to strategize and maintain a smooth flow of commerce in the product market. Data preprocessing is a crucial step that allows producers to gain insights into consumer behavior within their specific contexts. One effective approach is to employ machine algorithms to perform regression analysis, which can provide valuable insights into consumer behavior across different organizations and products. Presenting the results in graphical format can help convince management teams about the necessary actions to address any issues arising from customer behavior. Analytical data analysis tools play a vital role in providing the marketing team with a comprehensive understanding of ongoing market behavior. Categorization of data is crucial, as it enables the creation of variable distribution tables that highlight key aspects such as means and modes of purchasing patterns. By leveraging data analysis, businesses can gain a deeper understanding of customer behavior, identify areas of improvement, and develop targeted strategies to enhance customer satisfaction and loyalty. These analytical insights enable companies to make informed decisions and take proactive measures to address any shortcomings in their products, services, or overall customer experience.

VII. SUPPORT VECTOR MACHINE LEARNING ALGORITHM

Machine learning, an effective application of artificial intelligence, has gained significant traction in the telecom industry for evaluating and mitigating customer churn. One prominent machine learning algorithm used for churn prediction is the Support Vector Machine (SVM) algorithm [7]. SVM is a powerful supervised learning method that efficiently performs data analysis to predict churn. The SVM algorithm utilizes a series of techniques to separate data points effectively [8]. It works by mapping the data to create hyperplanes, with the optimal hyperplane being the one that maximally separates the data points. Figure 3 illustrates the concept of the optimal hyperplane in the SVM algorithm. By leveraging SVM, telecom companies can analyze customer data and identify patterns that indicate potential churn. The algorithm learns from historical data, including customer demographics, usage patterns, and behaviors, to build a model that can predict future churn events. This predictive capability enables businesses to take proactive measures to retain customers and minimize churn. Implementing SVM for churn prediction involves several steps. First, the historical data is collected and preprocessed, ensuring it is in a suitable format for analysis. Then, the SVM model is trained on the data, with features such as customer characteristics, usage patterns, and other relevant factors being used to predict churn. The model is optimized by adjusting parameters to maximize its accuracy and performance. Once the model is trained, it can be applied to new data to make churn predictions and classify customers as potential churners or non-churners.

Fig. 3. Optimal Hyperplane in SVM



Furthermore, those data points are mapped to higher dimensional space for identifying the suitable hyper planes among the instances of several classes. The new instances are classified into specific classes depending upon their proximity[9]. The mapping functions used in this algorithm are generally obtained from a combination of labeled training data set, such as, $\{x_i, y_i\}_{i=1, \dots, n}$. Hence, the modeling objective for finding the linear decision function can be described as follows;

$$(1) \quad f(x) = \langle w, \phi_i(x) \rangle + b$$

In the above equation,

w = weight vector

ϕ = nonlinear mapping function b = constant

This particular regression problem is formulated for minimizing the below risk function

$$R(C) = \frac{C}{n} \sum_{i=1}^n L_\varepsilon(f(x_i), y_i) + \frac{1}{2} \|w\|^2 \quad (2)$$

In the above equation,

$$L_\varepsilon(f(x), y) = \begin{cases} |f(x) - y| - \varepsilon & |f(x) - y| \geq \varepsilon \\ 0 & \text{otherwise} \end{cases}$$

(3)

= intensive loss function and,

After introducing the slack variables, Minimize:

(4)

$$R(w, \xi_i^*) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n (\xi_i + \xi_i^*)$$

Subject to:

$$(5) \quad \begin{cases} y_i - \langle w, x_i \rangle - b \leq \varepsilon + \xi_i \\ \langle w, x_i \rangle + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases}$$

In the above, C is the regularized constant having value greater than 0. This constant is taken to make a balance between the model flatness and training error. Moreover, this constant is responsible for representing penalty for any kind of prediction error. The objective of support vector is to minimize w^2 . Hence, the above equations can be changed by means of the lagrangian multiplies into one quadratic equation as follows;

$$(6) \quad f(x) = \sum_{i=1}^n (\alpha_i - \alpha_i^*) K(x_i, x) + b$$

$K(\cdot)$ represents a Kernel function, which value calculated by the inner products of the vectors x_i and x_j , which represented by the feature space $\phi(x_i)$ and $\phi(x_j)$. α_i^* and α_i represents the lagrange multiplies. These multipliers are subjected to the following;

$$\begin{aligned} \sum_{i=1}^n (\alpha_i - \alpha_i^*) &= 0 \\ 0 \leq \alpha_i \leq C \quad & i = 1, \dots, n \\ 0 \leq \alpha_i^* \leq C \quad & i = 1, \dots, n \end{aligned}$$

(7)

Furthermore, the kernel function satisfies Mercer’s condition. Hence,

(8)

There exist several useful kernel functions; however, the radial basic kernel function will become beneficial in classifying the customer churn in the telecommunication industries. This radial basic kernel function is represented by

(9)

$$K(x_i, x_j) = \exp(-|x_j - x_i|^2 / 2p^2)$$

The accuracy of an SVM model relies on the careful selection of its associated parameters. Parameters such as the error trade-off parameter (C) and the parameter controlling the width of the intensive zone require cross-validation for optimal tuning. The support vector machine (SVM) algorithm is a powerful prediction method for identifying churn rates. Unlike traditional churn prediction methods, SVM allows the solution to depend on subsets of the dataset, providing computational advantages [10]. Moreover, SVM focuses on minimizing generalization error rather than training error, which is a key factor in its adoption for churn prediction in the telecom industry. Fig. 4 illustrates the SVM-based framework used for churn prediction.

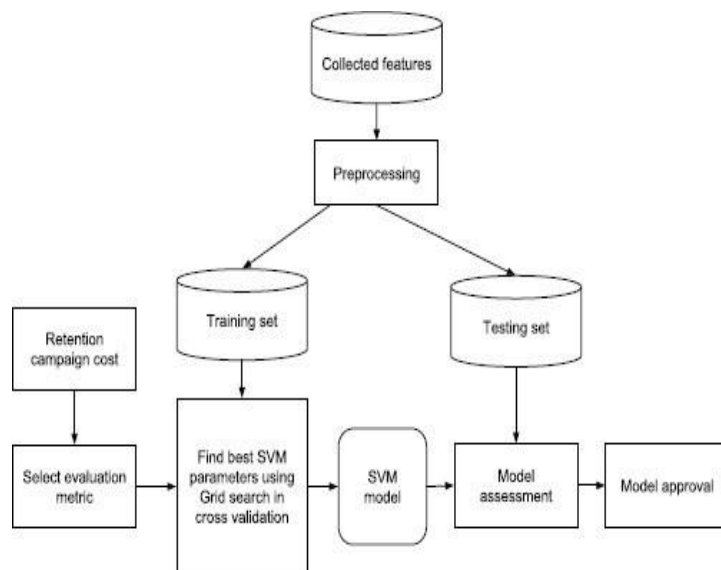


Fig. 4. Churn Prediction Framework

Therefore, based on the preceding discussion, it can be concluded that customer churn is a significant concern for all types of organizations. Ensuring customer retention is crucial for maintaining customer loyalty, which can be achieved by understanding their demands and serving them accordingly. The implementation of a powerful churn prediction model aids organizational management in effectively predicting customer churn. In the context of the telecommunication industry, which deals with complex data, the utilization of support vector machines (SVM) can prove highly advantageous for accurately predicting churn rates. SVM is a machine learning algorithm that can effectively analyze and interpret intricate telecom data, enabling organizations to identify potential churners. By leveraging the capabilities of SVM, companies can take proactive measures to prevent customer churn and enhance customer retention.

This report has primarily focused on the concept of customer retention in conjunction with churn prediction. It emphasizes the importance of understanding customer needs and preferences to foster loyalty. Additionally, the use of support vector machines has been highlighted as a valuable tool for improving churn prediction accuracy and facilitating proactive customer retention strategies. In conclusion, organizations across industries need to prioritize customer churn as a critical factor affecting their success. Customer retention, achieved through an understanding of customer demands and the implementation of powerful churn prediction models, plays a vital role in maintaining



customer loyalty. In the specific context of the telecommunication industry, the use of support vector machines can effectively predict churn rates by leveraging complex data. By adopting these strategies and incorporating SVM algorithms, companies can enhance customer retention and drive long-term business growth.

CONCLUSION

In conclusion, customer churn is a significant concern for organizations across all industries. The process of customer retention, which involves understanding customer demands and providing tailored services, plays a crucial role in maintaining customer loyalty. The implementation of a powerful churn prediction model can assist organizational management in accurately forecasting customer churn.

In the telecommunication industry, where complex data is abundant, support vector machine (SVM) algorithms have proven advantageous for predicting churn rates. By leveraging the capabilities of SVM, organizations can effectively analyze and interpret intricate telecom data, enabling them to identify potential churners and take proactive measures to prevent customer attrition. This report has focused on the importance of customer retention and churn prediction. It underscores the need for organizations to understand customer needs and preferences in order to foster loyalty. Additionally, the use of support vector machines has been highlighted as a valuable tool for improving churn prediction accuracy and facilitating proactive customer retention strategies.

In summary, organizations must prioritize customer churn as a critical factor that impacts their overall success. By prioritizing customer retention and employing powerful churn prediction models, organizations can effectively mitigate customer churn and enhance customer loyalty. The adoption of support vector machines in churn prediction, particularly in the telecommunication industry, can provide valuable insights and drive long-term business growth.

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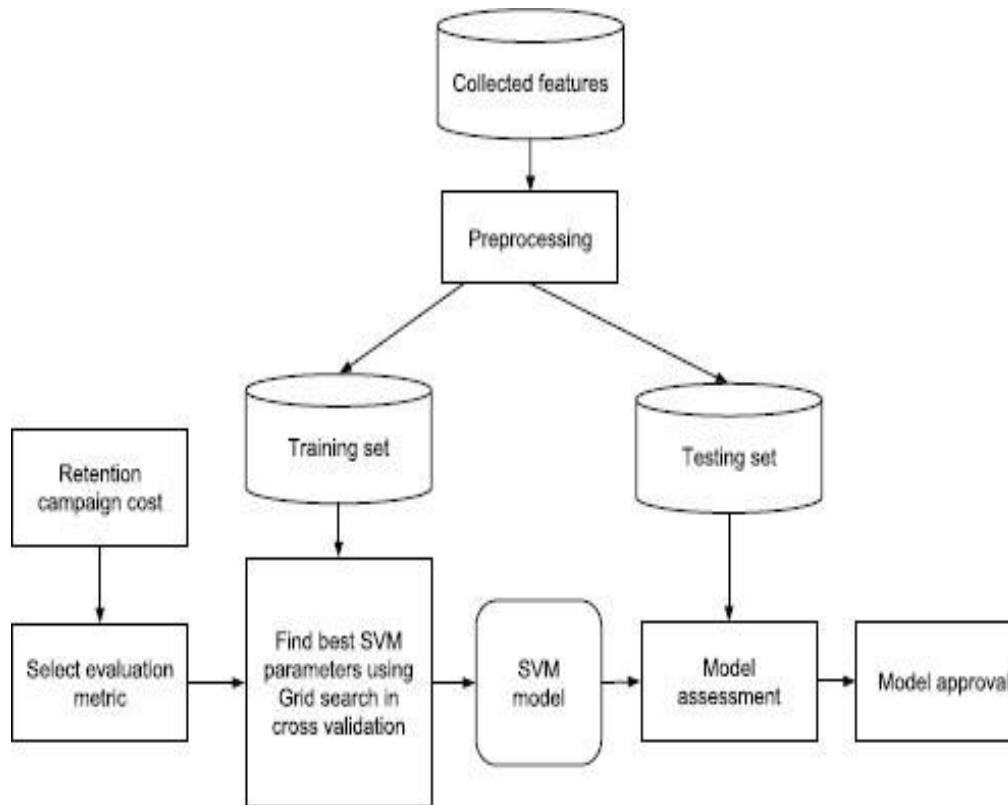


Fig. 4. Churn Prediction Framework

OUTPUT

Customer Churn Prediction Using Artificial Neural Network (ANN)

Customer churn prediction is to measure why customers are leaving a business. In this tutorial we will be looking at customer churn in telecom business. We will build a deep learning model to predict the churn and use precision, recall, f1-score to measure performance of our model

```

In [251]: import pandas as pd
          from matplotlib import pyplot as plt
          import numpy as np
          %matplotlib inline

Load the data

In [252]: df = pd.read_csv("customer_churn.csv")
          df.sample(5)

Out[252]:
   customerID  gender  SeniorCitizen  Partner  Dependents  tenure  PhoneService  MultipleLines  InternetService  OnlineSecurity  ...  DeviceProtection  TechSupp
6535  0520-  FDVVT    Male            0      No          No       35             Yes           No             Fiber optic      No  ...             Yes           I
5527  5985-  BEHZK    Female          1      Yes          No       72             Yes           Yes             Fiber optic      No  ...             Yes           I
668   3859-  CVCET    Female          0      No          No        4             Yes           No              DSL             No  ...             No           I
4822  2664-  XJZNO    Male            0      Yes          Yes       72             Yes           No             Fiber optic      Yes  ...             Yes           \
6850  0531-  XBKMM    Male            0      No          Yes       66             Yes           Yes             DSL             Yes  ...             No           \

5 rows × 21 columns
  
```


Data Visualization

In [271]...

```
tenure_churn_no = df1[df1.Churn=='No'].tenure
tenure_churn_yes = df1[df1.Churn=='Yes'].tenure

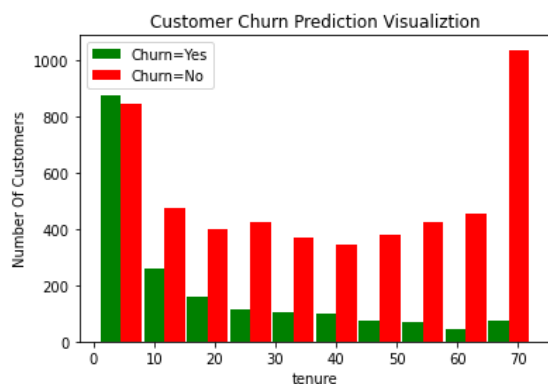
plt.xlabel("tenure")
plt.ylabel("Number Of Customers")
plt.title("Customer Churn Prediction Visualiztion")

blood_sugar_men = [113, 85, 90, 150, 149, 88, 93, 115, 135, 80, 77, 82, 129]
blood_sugar_women = [67, 98, 89, 120, 133, 150, 84, 69, 89, 79, 120, 112, 100]

plt.hist([tenure_churn_yes, tenure_churn_no], rwidth=0.95, color=['green', 'red'], label=['Churn=Yes', 'Churn=No'])
plt.legend()
```

Out[271]...

<matplotlib.legend.Legend at 0x2181d04b700>



In [272]...

```
mc_churn_no = df1[df1.Churn=='No'].MonthlyCharges
mc_churn_yes = df1[df1.Churn=='Yes'].MonthlyCharges

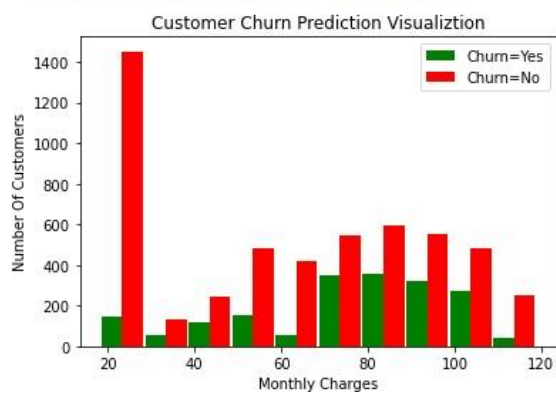
plt.xlabel("Monthly Charges")
plt.ylabel("Number Of Customers")
plt.title("Customer Churn Prediction Visualiztion")

blood_sugar_men = [113, 85, 90, 150, 149, 88, 93, 115, 135, 80, 77, 82, 129]
blood_sugar_women = [67, 98, 89, 120, 133, 150, 84, 69, 89, 79, 120, 112, 100]

plt.hist([mc_churn_yes, mc_churn_no], rwidth=0.95, color=['green', 'red'], label=['Churn=Yes', 'Churn=No'])
plt.legend()
```

Out[272]...

<matplotlib.legend.Legend at 0x2181d15fac0>

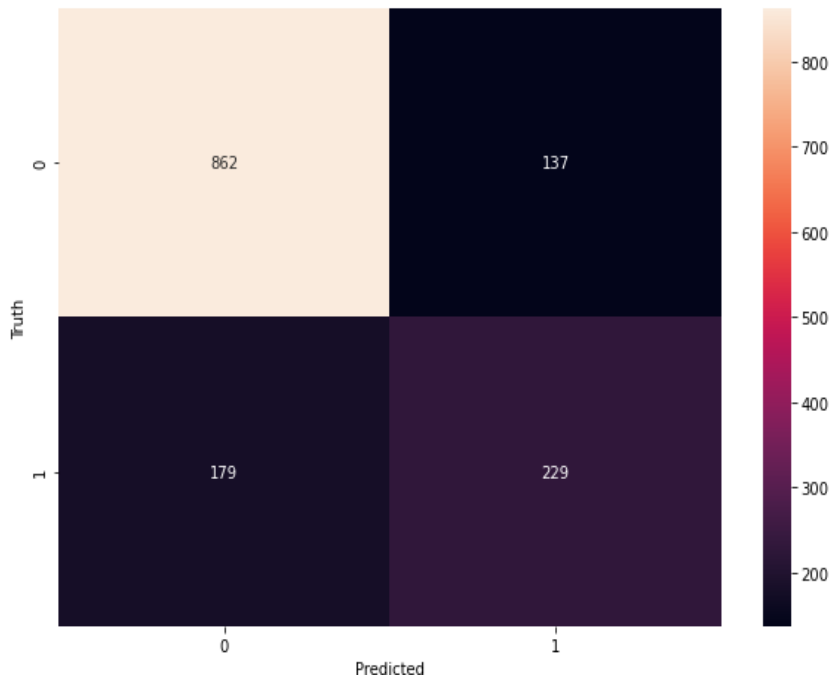


In [222...]

```
import seaborn as sn
cm = tf.math.confusion_matrix(labels=y_test,predictions=y_pred)

plt.figure(figsize = (10,7))
sn.heatmap(cm, annot=True, fmt='d')
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

Out[222... Text(69.0, 0.5, 'Truth')]



CONCLUSION

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In summary, organizations must prioritize customer churn as a critical factor that impacts their overall success. By prioritizing customer retention and employing powerful churn prediction models, organizations can effectively mitigate customer churn and enhance customer loyalty. The adoption of support vector machines in churn prediction, particularly in the telecommunication industry, can provide valuable insights and drive long-term business growth.

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