

The SyraTel dataset was chosen due to its relevance to the telecommunications industry. It includes information about customer interactions, service usage, and other key metrics. This dataset is crucial for understanding customer behavior, predicting trends, and optimizing business processes.

# Modeling *∂*

In the modeling phase, we employed a range of analytical techniques to extract meaningful insights from the SyraTel dataset. The detailed code and implementation are available in the accompanying Jupyter Notebook within this repository.

Our initial approach involved utilizing Logistic Regression as the first model. While achieving a satisfactory accuracy of 85%, we recognized the potential for improvement. Subsequently, we introduced additional models to enhance performance and push the boundaries of predictive accuracy. The pursuit of optimal outcomes remains a central focus in our modeling endeavors. At last, we arrived at Rondom Forest. The Metrices are as shown below.

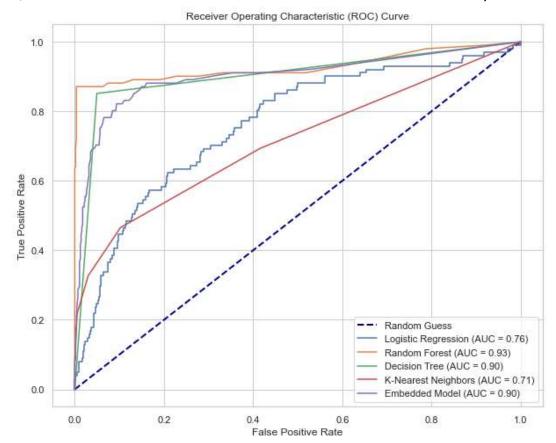
Random Forest Random Forest				
	precision	recall	f1-score	support
False	0.97	1.00	0.99	566
True	0.98	0.85	0.91	101
accuracy			0.97	667
macro avg	0.98	0.92	0.95	667
weighted avg	0.97	0.97	0.97	667

## Model Evaluation *∂*

In the evaluation phase, we conducted an exhaustive examination of model performance and the overall effectiveness of our analysis. Rigorous testing was executed against various models, including Logistic Regression, Random Forest, Decision Tree, K-Nearest Neighbour, and Ensemble Method.

Upon careful evaluation, Random Forest emerged as the most robust model for our dataset, boasting impressive metrics: accuracy of 97%, precision of 97%, and recall of 97%. This selection signifies the model's exceptional ability to accurately predict and classify outcomes.

Additionally, we employed the Synthetic Minority Oversampling Technique (SMOTE) to address imbalances in the dataset. Specifically, we oversampled the minority class "True," representing customers who churned. This strategic enhancement ensures a more robust and balanced training dataset, contributing to the model's enhanced performance and reliability. The results is as shown below:



# Conclusion 2

- customer service calls: The frquency of a customer calling customer service ether to raise a concern over the service or requesting for assistance.
- international plan: This is binary value that indicates that a customer has interbatianal call plans or not
- Total Cost: This is the sum of day\_charge , evening\_charge, and night\_charge to get a 24 hours cost of calls
- Total Day minutes: amount of time in minutes spent by costomers on call
- Total day charge: this is the amount of money spent by the users while on call during the day. Probaly the price rate per minute during day is expensive thus leading to churn

# Recommendations @

## Review Call Charges:

- Evaluate the pricing structure for calls, especially during the day, and consider revising it to make it more competitive and customer-friendly.
- Introduce promotions or packages that offer cost-effective calling plans, potentially reducing the incentive for customers to churn.

**Enhance Customer Service Experience:** 

- Invest in customer service training to ensure representatives are well-equipped to address and resolve customer issues efficiently.
- Implement measures to reduce customer service wait times, such as increasing staff during peak hours or optimizing the customer care queue system.

Improve Communication with Customers:

- Enhance communication channels to keep customers informed about the status of their service requests, reducing frustration and the need for frequent customer service calls.
- Consider implementing automated systems to provide updates on common issues, allowing customers to get information without having to contact customer service.

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