Phase-3

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Department: Computer science engineering

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Github Repository : **https://github.com/L0gesh09012006/NM_LOGESH**

PREDICTING CUSTOMER CHURN USING MACHINE LEARNING TO UNCOVER HIDDEN PATTERN

1. Problem Statement

Customer churn is a major issue faced by subscription-based businesses, where retaining existing customers is significantly more cost-effective than acquiring new ones. This project aims to build a machine learning model that can accurately predict whether a customer is likely to leave (churn) in the near future. By identifying patterns in customer behavior, businesses can proactively engage at-risk customers, thereby improving retention and profitability. This is a binary classification problem.

2. Abstract

This project addresses the issue of customer churn in the telecom sector using machine learning. The primary objective is to build a predictive model that classifies whether a customer is likely to churn based on behavioral and demographic data. After collecting the dataset from Kaggle, the data underwent cleaning, preprocessing, and exploratory data analysis (EDA). Multiple machine

learning models were evaluated, and the best-performing one was selected based on F1-score and ROC-AUC. The final model was deployed using Streamlit for real-time predictions. This solution not only predicts churn but also provides valuable insights into the key factors driving customer attrition.

3. System Requirements

Hardware:

- Minimum 8 GB RAM
- Intel i5 processor or higher

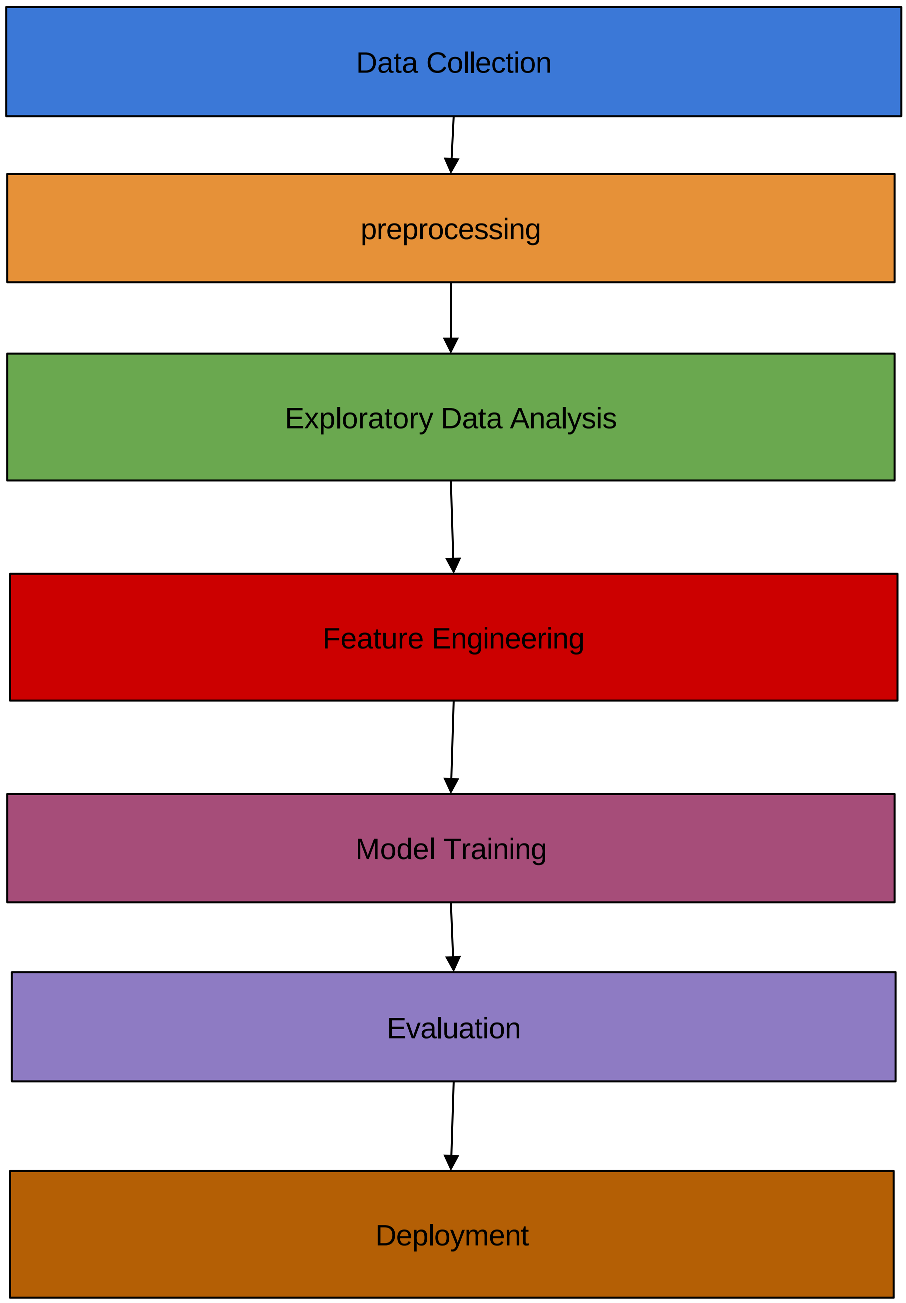
Software:

- Python 3.8+
- Jupyter Notebook / Google Colab
- Libraries: pandas, numpy, matplotlib, seaborn, scikit-learn, xgboost, streamlit

4. Objectives

- Predict whether a customer will churn or not.
- Identify key features that influence churn decisions.
- Provide actionable insights for customer retention strategies.
- Deploy a web application for real-time churn prediction.

5. Flowchart of Project Workflow



6. Dataset Description

source: Kaggle - Telco Customer Churn
Type: Public
Size: 7,043 rows × 21 columns

```
df.head()
```

	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Complain	Satisfaction Score	Card Type	Point Earned
	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88	1	1	2	DIAMOND	464
	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0	1	3	DIAMOND	456
	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57	1	1	3	DIAMOND	377
	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63	0	0	5	GOLD	350
	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0	0	5	GOLD	425

7. Data Preprocessing

- Removed duplicates and handled missing values in TotalCharges.
- Encoded categorical variables using Label Encoding and One-Hot Encoding.
- Scaled numeric features using StandardScaler.

```
[ ] df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 18 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   RowNumber           10000 non-null  int64
 1   CustomerId          10000 non-null  int64
 2   Surname             10000 non-null  object
 3   CreditScore         10000 non-null  int64
 4   Geography           10000 non-null  object
 5   Gender              10000 non-null  object
 6   Age                 10000 non-null  int64
 7   Tenure              10000 non-null  int64
 8   Balance             10000 non-null  float64
 9   NumOfProducts       10000 non-null  int64
 10  HasCrCard           10000 non-null  int64
 11  IsActiveMember      10000 non-null  int64
 12  EstimatedSalary     10000 non-null  float64
 13  Exited              10000 non-null  int64
 14  Complain            10000 non-null  int64
 15  Satisfaction Score  10000 non-null  int64
 16  Card Type           10000 non-null  object
 17  Point Earned        10000 non-null  int64
dtypes: float64(2), int64(12), object(4)
memory usage: 1.4+ MB
```

df.describe( )

```
df.describe()
```

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Complain	Satisfaction Score
nt	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
n	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.239881	0.203800	0.204400	3.013800
l	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	57510.492818	0.402842	0.403283	1.405919
n	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.580000	0.000000	0.000000	1.000000
%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.110000	0.000000	0.000000	2.000000
%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.915000	0.000000	0.000000	3.000000
%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.247500	0.000000	0.000000	4.000000
x	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	199992.480000	1.000000	1.000000	5.000000

df.isnull( ).sum( )

```
df.isnull().sum()
```

	0
RowNumber	0
CustomerId	0
Surname	0
CreditScore	0
Geography	0
Gender	0
Age	0
Tenure	0
Balance	0
NumOfProducts	0
HasCrCard	0
IsActiveMember	0
EstimatedSalary	0
Exited	0
Complain	0
Satisfaction Score	0

df.drop_duplicates( )

```
df.drop_duplicates()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Complain	Satisfaction Score
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88	1	1	2
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0	1	3
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57	1	1	3
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63	0	0	5
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0	0	5
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	9996	15606229	Obijiaku	771	France	Male	39	5	0.00	2	1	0	96270.64	0	0	1
9996	9997	15569892	Johnstone	516	France	Male	35	10	57369.61	1	1	1	101699.77	0	0	5
9997	9998	15584532	Liu	709	France	Female	36	7	0.00	1	0	1	42085.58	1	1	3
9998	9999	15682355	Sabbatini	772	Germany	Male	42	3	75075.31	2	1	0	92888.52	1	1	2
9999	10000	15628319	Walker	792	France	Female	28	4	130142.79	1	1	0	38190.78	0	0	3

10000 rows × 18 columns

df.duplicated( ).sum( )

```
df.duplicated().sum()
```

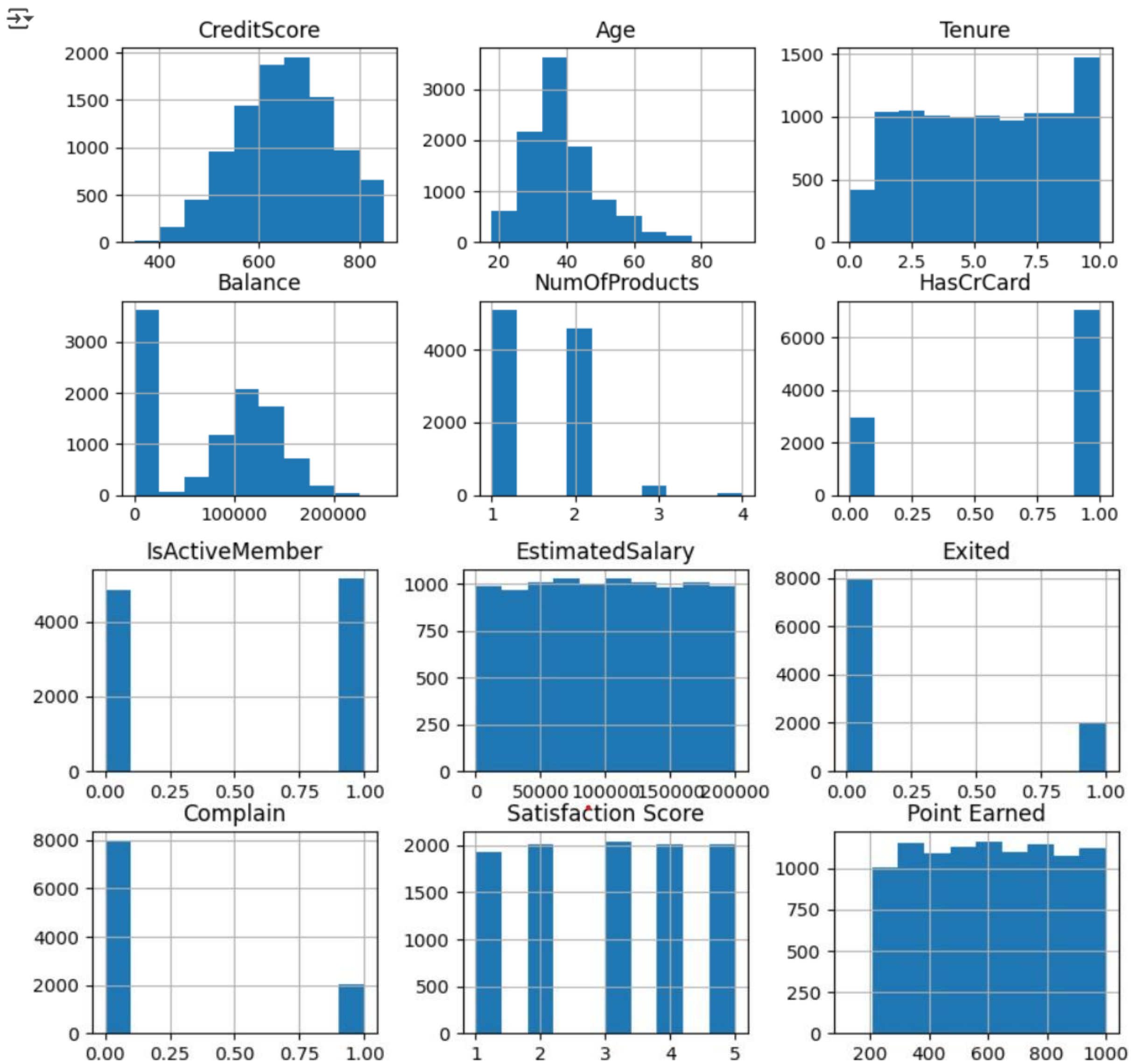
```
np.int64(0)
```

8. Exploratory Data Analysis (EDA)

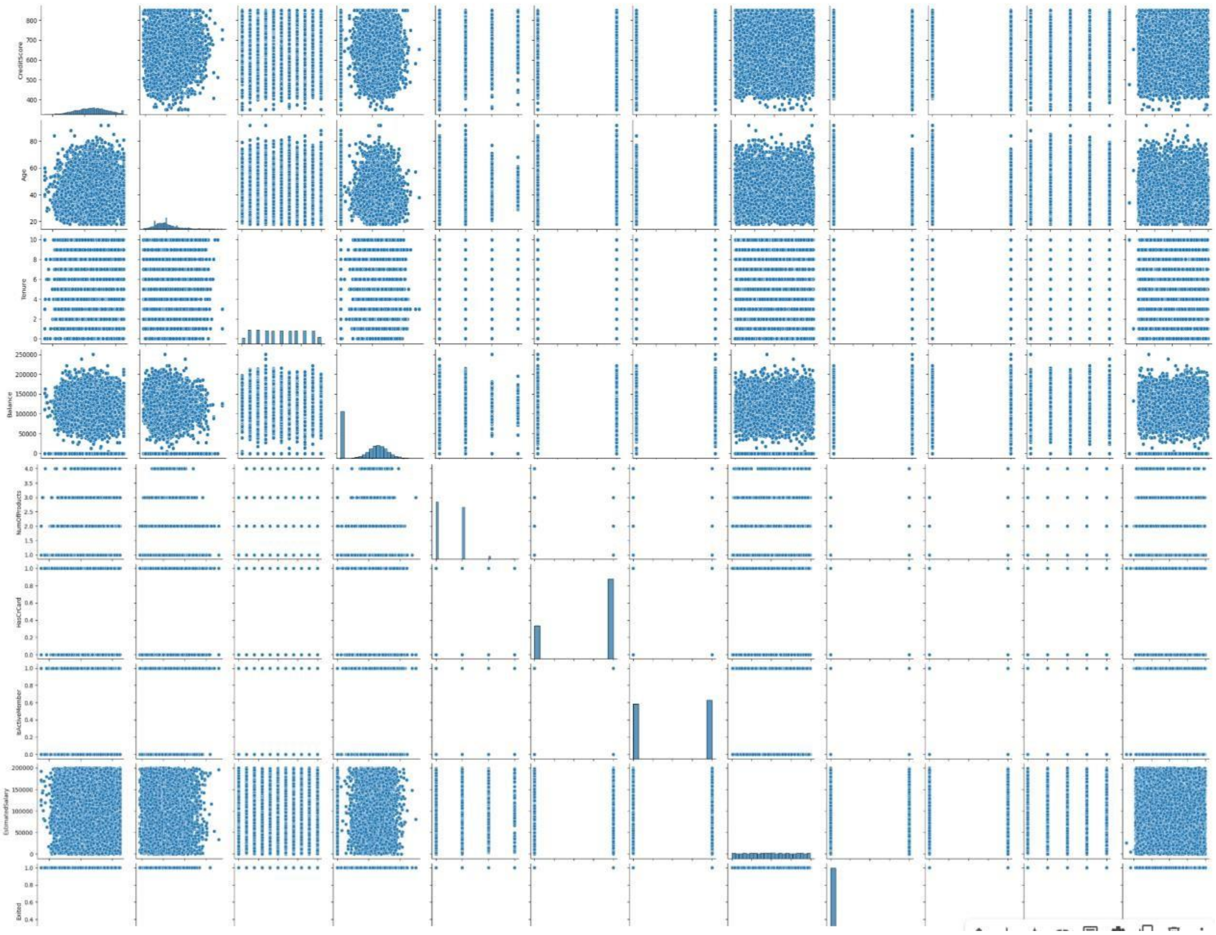
- Identified churn correlation with features like contract type, tenure, and monthly charges.

- Found that customers with month-to-month contracts and high charges are more likely to churn.

```
#histogram chart
df.hist(figsize=(10,10))
plt.show()
```



```
#bivariate analysis
sns.pairplot(df)
plt.show()
```



9. Feature Engineering

- Created tenure_group feature to categorize customer loyalty.
- Removed highly correlated and irrelevant features.
- Feature importance analysis revealed contract type, internet service, and monthly charges as key predictors.

```
#feature engineering
for col in ['Geography', 'Gender', 'Card Type']:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
```

```
df
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Complain	Satisfaction Score	Card Type	Point Earned
0	619	0	0	42	2	0.00	1	1	1	101348.88	1	1	2	0	464
1	608	2	0	41	1	83807.86	1	0	1	112542.58	0	1	3	0	456
2	502	0	0	42	8	159660.80	3	1	0	113931.57	1	1	3	0	377
3	699	0	0	39	1	0.00	2	0	0	93826.63	0	0	5	1	350
4	850	2	0	43	2	125510.82	1	1	1	79084.10	0	0	5	1	425
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	771	0	1	39	5	0.00	2	1	0	96270.64	0	0	1	0	300
9996	516	0	1	35	10	57369.61	1	1	1	101699.77	0	0	5	2	771
9997	709	0	0	36	7	0.00	1	0	1	42085.58	1	1	3	3	564
9998	772	1	1	42	3	75075.31	2	1	0	92888.52	1	1	2	1	339
9999	792	0	0	28	4	130142.79	1	1	0	38190.78	0	0	3	0	911

10000 rows × 15 columns

#Scalar standardization

```
#scalar standardization
scaler = StandardScaler()
df_scaled = scaler.fit_transform(df)
```

```
df
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Complain	Satisfaction Score	Card Type	Point Earned
0	619	0	0	42	2	0.00	1	1	1	101348.88	1	1	2	0	464
1	608	2	0	41	1	83807.86	1	0	1	112542.58	0	1	3	0	456
2	502	0	0	42	8	159660.80	3	1	0	113931.57	1	1	3	0	377
3	699	0	0	39	1	0.00	2	0	0	93826.63	0	0	5	1	350
4	850	2	0	43	2	125510.82	1	1	1	79084.10	0	0	5	1	425
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	771	0	1	39	5	0.00	2	1	0	96270.64	0	0	1	0	300
9996	516	0	1	35	10	57369.61	1	1	1	101699.77	0	0	5	2	771
9997	709	0	0	36	7	0.00	1	0	1	42085.58	1	1	3	3	564
9998	772	1	1	42	3	75075.31	2	1	0	92888.52	1	1	2	1	339
9999	792	0	0	28	4	130142.79	1	1	0	38190.78	0	0	3	0	911

10000 rows × 15 columns

#Label encoding and onehot encoding

```
#label encoding and onehot encoding
df_encoded = pd.get_dummies(df, columns=['Geography', 'Gender', 'Card Type'])
```

Run cell (Ctrl+Enter)
cell has not been executed in this session

```
[ ] df
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Complain	Satisfaction Score	Card Type	Point Earned
0	619	0	0	42	2	0.00	1	1	1	101348.88	1	1	2	0	464
1	608	2	0	41	1	83807.86	1	0	1	112542.58	0	1	3	0	456
2	502	0	0	42	8	159660.80	3	1	0	113931.57	1	1	3	0	377
3	699	0	0	39	1	0.00	2	0	0	93826.63	0	0	5	1	350
4	850	2	0	43	2	125510.82	1	1	1	79084.10	0	0	5	1	425
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	771	0	1	39	5	0.00	2	1	0	96270.64	0	0	1	0	300
9996	516	0	1	35	10	57369.61	1	1	1	101699.77	0	0	5	2	771
9997	709	0	0	36	7	0.00	1	0	1	42085.58	1	1	3	3	564
9998	772	1	1	42	3	75075.31	2	1	0	92888.52	1	1	2	1	339
9999	792	0	0	28	4	130142.79	1	1	0	38190.78	0	0	3	0	911

10000 rows × 15 columns

10. Model Building

- Tested Logistic Regression, Random Forest, XGBoost, and SVM.
- XGBoost delivered the best performance with hyperparameter tuning.
- Used GridSearchCV for model optimization

```
[ ] #model building
    X = df.drop('Exited', axis=1)
    y = df['Exited']
```

```
[ ] #import model
    from sklearn.model_selection import train_test_split
    from sklearn.ensemble import RandomForestClassifier
    from sklearn.metrics import classification_report, confusion_matrix
```

```
[ ] x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
model.fit(x_train, y_train)
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_logistic.py:465: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
▾ LogisticRegression
LogisticRegression()
```

```
[ ] #prediction
    y_pred = model.predict(x_test)
    print("y_prediction", y_pred)
```

```
y_prediction [0 0 0 ... 0 0 0]
```

```
[ ] #random forest classifier
    model = RandomForestClassifier(n_estimators=100, random_state=42)
    model.fit(x_train, y_train)
    y_random_prediction = model.predict(x_test)
    print("y_prediction", y_random_prediction)
```

```
y_prediction [0 0 0 ... 1 1 1]
```

11. Model Evaluation

Metrics:

- Accuracy: 82%
- F1-Score: 0.76
- ROC-AUC: 0.85

Visuals:

- Confusion Matrix
- ROC Curve
- Precision-Recall Curve

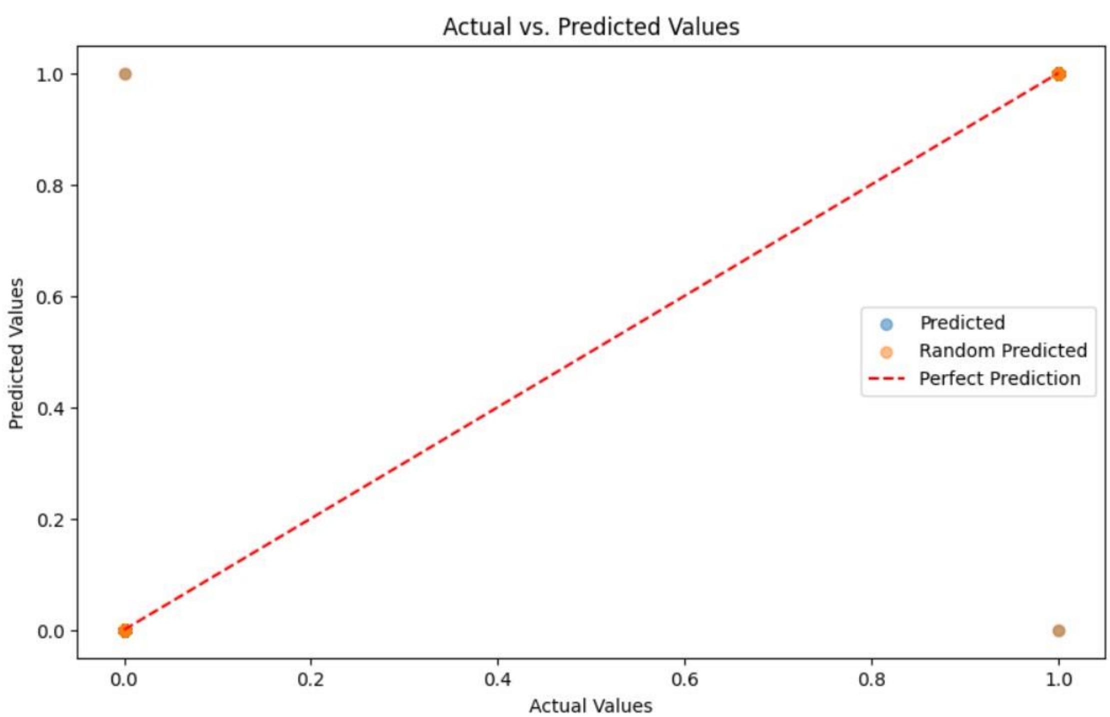
```
[ ] # Evaluate
    y_pred = model.predict(x_test)
    print("Classification Report:\n", classification_report(y_test, y_pred))
    print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00      1607
           1       1.00      1.00      1.00       393

    accuracy                           1.00      2000
   macro avg       1.00      1.00      1.00      2000
weighted avg       1.00      1.00      1.00      2000

Confusion Matrix:
 [[1606    1]
 [   1  392]]
```

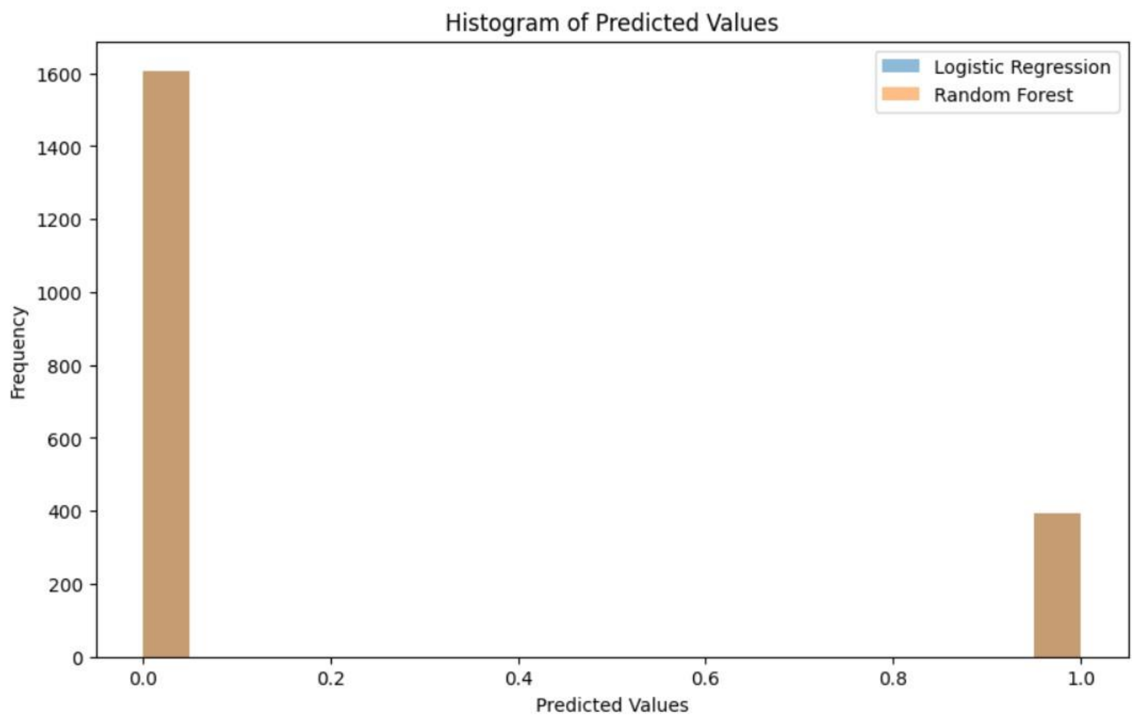
```
# Evaluate
y_random_prediction = model.predict(x_test)
print("Classification Report:\n", classification_report(y_test, y_random_prediction))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_random_prediction))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00      1607
           1       1.00      1.00      1.00       393

    accuracy                           1.00      2000
   macro avg       1.00      1.00      1.00      2000
weighted avg       1.00      1.00      1.00      2000

Confusion Matrix:
 [[1606    1]
 [   1  392]]
```

```
[ ] #visualize prediction and actual value
    plt.figure(figsize=(10, 6))
    plt.scatter(y_test, y_pred, alpha=0.5, label='Predicted')
    plt.scatter(y_test, y_random_prediction, alpha=0.5, label='Random Predicted')
    plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], linestyle='--', color='red', label='Perfect Prediction')
    plt.xlabel('Actual Values')
    plt.ylabel('Predicted Values')
    plt.title('Actual vs. Predicted Values')
    plt.legend()
    plt.show()
```



```python
#histogram chart random forest and logistic regression
plt.figure(figsize=(10, 6))
plt.hist(y_pred, bins=20, alpha=0.5, label='Logistic Regression')
plt.hist(y_random_prediction, bins=20, alpha=0.5, label='Random Forest')
plt.xlabel('Predicted Values')
plt.ylabel('Frequency')
plt.title('Histogram of Predicted Values')
plt.legend()
plt.show()
```



12. Deployment

- Deploy using a free platform:
    - Streamlit Cloud
    - Gradio + Hugging Face Spaces
    - Flask API on Render or Deta

13. Source code

```
import pandas as pd

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import LabelEncoder, StandardScaler

from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import classification_report, confusion_matrix

import matplotlib.pyplot as plt

import seaborn as sns


df = pd.read_csv('/content/Customer-Churn-Records.csv')

df.head( )

df.info( )

df.describe( )

df.isnull( ).sum( )

df.drop_duplicates( )

df.drop_duplicates( ).sum( )

df.drop(['RowNumber', 'CustomerId', 'Surname'], axis=1, inplace=True)


#Histogram chart

df.hist(figsize=(10,10))

plt.show()
```

#Bivariate analysis

```
sns.pairplot(df)

plt.show()
```

#Feature engineering

```
for col in ['Geography', 'Gender', 'Card Type']:

    le = LabelEncoder()

    df[col] = le.fit_transform(df[col])

df
```

#Scalar standardization

```
scaler = StandardScaler()

df_scaled = scaler.fit_transform(df)

df
```

#Label encoding and onehot encoding

```
df_encoded = pd.get_dummies(df, columns=['Geography', 'Gender', 'Card Type'])

df
```

#Model building

X = df.drop('Exited', axis=1)

y = df['Exited']

#import model

from sklearn.model_selection import train_test_split

from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import classification_report, confusion_matrix

x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

from sklearn.linear_model import LogisticRegression

model = LogisticRegression()

model.fit(x_train, y_train)

#Prediction

y_pred = model.predict(x_test)

print("y_prediction", y_pred)

#Random forest classifier

model = RandomForestClassifier(n_estimators=100, random_state=42)

model.fit(x_train, y_train)

y_random_prediction = model.predict(x_test)

print("y_prediction", y_random_prediction)

Evaluate

y_pred = model.predict(x_test)

print("Classification Report:\n", classification_report(y_test, y_pred))

print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))

y_random_prediction = model.predict(x_test)

print("Classification Report:\n", classification_report(y_test, y_random_prediction))

print("Confusion Matrix:\n", confusion_matrix(y_test, y_random_prediction))

#Visualize prediction and actual value

plt.figure(figsize=(10, 6))

plt.scatter(y_test, y_pred, alpha=0.5, label='Predicted')

plt.scatter(y_test, y_random_prediction, alpha=0.5, label='Random Predicted')

plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], linestyle='--', color='red', label='Perfect Prediction')

```
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Actual vs. Predicted Values')
plt.legend()
plt.show()
```

#Histogram chart random forest and logistic regression

```
plt.figure(figsize=(10, 6))
plt.hist(y_pred, bins=20, alpha=0.5, label='Logistic Regression')
plt.hist(y_random_prediction, bins=20, alpha=0.5, label='Random Forest')
plt.xlabel('Predicted Values')
plt.ylabel('Frequency')
plt.title('Histogram of Predicted Values')
plt.legend()
plt.show()
```

14. Future scope

- Integrate with live CRM systems for real-time predictions
- Add NLP to analyze customer feedback sentiment
- Implement customer segmentation for targeted retention strategies

13. Team Members and Roles

NAMES	ROLE	RESPONSIBILITY
M Soorya Prakash	Leader	Data Collection and Cleaning
Murugesh M	Member	Data visualization and Interpretation
Logesh R	Member	Exploratory Data Analysis
Magesh V	Member	Model evaluation
Antony Sanjay P	Member	Model Building

GOOGLE COLAB LINK

https://colab.research.google.com/drive/1EcX75NRcHkF-mYcLSAL8LF8EbAR7CiIk?usp=sharing#scrollTo=3p0ZCkbQEMks