

Task 1:- Data Preprocessing

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import LabelEncoder

# Load dataset
telco = pd.read_csv('/content/Telco_Customer_Churn_Dataset.csv')

#missing Value
print("\nMissing value in each column: ")
telco.isnull().sum()
```

Missing value in each column:

customerID	0
gender	0
SeniorCitizen	0
Partner	0
Dependents	0
tenure	0
PhoneService	0
MultipleLines	0
InternetService	0
OnlineSecurity	0
OnlineBackup	0
DeviceProtection	0
TechSupport	0
StreamingTV	0
StreamingMovies	0
Contract	0
PaperlessBilling	0
PaymentMethod	0
MonthlyCharges	0
TotalCharges	0
Churn	0

dtype: int64

```
#One Hot Encoding
telco['TotalCharges'] = pd.to_numeric(telco['TotalCharges'],
errors='coerce')
telco['TotalCharges'] =
telco['TotalCharges'].fillna(telco['TotalCharges'].median())

from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
telco['Churn'] = le.fit_transform(telco['Churn'])
```

```
telco = telco.drop(columns=['customerID'])

# One-Hot Encode to all categorical variables
telco = pd.get_dummies(telco, drop_first=True)
```

```
print(telco.info())
```

```
telco = telco.astype('float64')
```

```
print(telco.dtypes)
```

```
print(telco.head())
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 7043 entries, 0 to 7042
```

```
Data columns (total 31 columns):
```

#	Column	Non-Null Count	Dtype
0	SeniorCitizen	7043 non-null	int64
1	tenure	7043 non-null	int64
2	MonthlyCharges	7043 non-null	float64
3	TotalCharges	7043 non-null	float64
4	Churn	7043 non-null	int64
5	gender_Male	7043 non-null	bool
6	Partner_Yes	7043 non-null	bool
7	Dependents_Yes	7043 non-null	bool
8	PhoneService_Yes	7043 non-null	bool
9	MultipleLines_No phone service	7043 non-null	bool
10	MultipleLines_Yes	7043 non-null	bool
11	InternetService_Fiber optic	7043 non-null	bool
12	InternetService_No	7043 non-null	bool
13	OnlineSecurity_No internet service	7043 non-null	bool
14	OnlineSecurity_Yes	7043 non-null	bool
15	OnlineBackup_No internet service	7043 non-null	bool
16	OnlineBackup_Yes	7043 non-null	bool
17	DeviceProtection_No internet service	7043 non-null	bool
18	DeviceProtection_Yes	7043 non-null	bool
19	TechSupport_No internet service	7043 non-null	bool
20	TechSupport_Yes	7043 non-null	bool
21	StreamingTV_No internet service	7043 non-null	bool
22	StreamingTV_Yes	7043 non-null	bool
23	StreamingMovies_No internet service	7043 non-null	bool
24	StreamingMovies_Yes	7043 non-null	bool
25	Contract_One year	7043 non-null	bool
26	Contract_Two year	7043 non-null	bool
27	PaperlessBilling_Yes	7043 non-null	bool
28	PaymentMethod_Credit card (automatic)	7043 non-null	bool
29	PaymentMethod_Electronic check	7043 non-null	bool
30	PaymentMethod_Mailed check	7043 non-null	bool

dtypes: bool(26), float64(2), int64(3)

memory usage: 454.1 KB

None

SeniorCitizen	float64
tenure	float64
MonthlyCharges	float64
TotalCharges	float64
Churn	float64
gender_Male	float64
Partner_Yes	float64
Dependents_Yes	float64
PhoneService_Yes	float64
MultipleLines_No phone service	float64
MultipleLines_Yes	float64
InternetService_Fiber optic	float64
InternetService_No	float64
OnlineSecurity_No internet service	float64
OnlineSecurity_Yes	float64
OnlineBackup_No internet service	float64
OnlineBackup_Yes	float64
DeviceProtection_No internet service	float64
DeviceProtection_Yes	float64
TechSupport_No internet service	float64
TechSupport_Yes	float64
StreamingTV_No internet service	float64
StreamingTV_Yes	float64
StreamingMovies_No internet service	float64
StreamingMovies_Yes	float64
Contract_One year	float64
Contract_Two year	float64
PaperlessBilling_Yes	float64
PaymentMethod_Credit card (automatic)	float64
PaymentMethod_Electronic check	float64
PaymentMethod_Mailed check	float64

dtype: object

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges	Churn
gender_Male \					
0	0.0	1.0	29.85	29.85	0.0
0.0					
1	0.0	34.0	56.95	1889.50	0.0
1.0					
2	0.0	2.0	53.85	108.15	1.0
1.0					
3	0.0	45.0	42.30	1840.75	0.0
1.0					
4	0.0	2.0	70.70	151.65	1.0
0.0					

Partner_Yes Dependents_Yes PhoneService_Yes \

0	1.0	0.0	0.0
1	0.0	0.0	1.0
2	0.0	0.0	1.0
3	0.0	0.0	0.0
4	0.0	0.0	1.0

MultipleLines_No phone service ... StreamingTV_No internet service \

0	1.0	...
0.0		
1	0.0	...
0.0		
2	0.0	...
0.0		
3	1.0	...
0.0		
4	0.0	...
0.0		

StreamingTV_Yes StreamingMovies_No internet service StreamingMovies_Yes \

0	0.0	0.0
0.0		
1	0.0	0.0
0.0		
2	0.0	0.0
0.0		
3	0.0	0.0
0.0		
4	0.0	0.0
0.0		

Contract_One year Contract_Two year PaperlessBilling_Yes \

0	0.0	0.0	1.0
1	1.0	0.0	0.0
2	0.0	0.0	1.0
3	1.0	0.0	0.0
4	0.0	0.0	1.0

PaymentMethod_Credit card (automatic) PaymentMethod_Electronic check \

0	0.0
1.0	
1	0.0
0.0	
2	0.0
0.0	
3	0.0
0.0	
4	0.0

1.0

	PaymentMethod_Mailed	check
0		0.0
1		1.0
2		1.0
3		0.0
4		0.0

[5 rows x 31 columns]

Task 2 :-Split Data for Training and Testing

```
from sklearn.model_selection import train_test_split
X = telco.drop('Churn', axis=1) # Features
y = telco['Churn'] # Target variable
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size =
0.2, random_state = 1)
print(X_train)
print(X_test)
print(y_train)
print(y_test)
```

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges	gender_Male
\ 1814	0.0	12.0	19.70	258.35	1.0
5946	0.0	42.0	73.90	3160.55	0.0
3881	0.0	71.0	65.15	4681.75	1.0
2389	0.0	71.0	85.45	6300.85	1.0
3676	0.0	30.0	70.40	2044.75	1.0
...
905	1.0	9.0	100.50	918.60	1.0
5192	0.0	60.0	19.95	1189.90	1.0
3980	0.0	28.0	105.70	2979.50	1.0
235	0.0	2.0	54.40	114.10	1.0
5157	0.0	16.0	68.25	1114.85	0.0

	Partner_Yes	Dependents_Yes	PhoneService_Yes	\
1814	1.0	1.0	1.0	

5946	0.0	0.0	1.0
3881	1.0	0.0	1.0
2389	1.0	1.0	1.0
3676	0.0	0.0	1.0
...
905	0.0	0.0	1.0
5192	0.0	1.0	1.0
3980	0.0	0.0	1.0
235	0.0	0.0	1.0
5157	1.0	1.0	1.0

	MultipleLines_No phone service	MultipleLines_Yes	...	\
1814	0.0	0.0	...	
5946	0.0	0.0	...	
3881	0.0	1.0	...	
2389	0.0	1.0	...	
3676	0.0	0.0	...	
...	
905	0.0	1.0	...	
5192	0.0	0.0	...	
3980	0.0	1.0	...	
235	0.0	1.0	...	
5157	0.0	0.0	...	

	StreamingTV_No internet service	StreamingTV_Yes	\
1814	1.0	0.0	
5946	0.0	0.0	
3881	0.0	0.0	
2389	0.0	1.0	
3676	0.0	1.0	
...	
905	0.0	1.0	
5192	1.0	0.0	
3980	0.0	1.0	
235	0.0	0.0	
5157	0.0	0.0	

	StreamingMovies_No internet service	StreamingMovies_Yes	\
1814	1.0	0.0	
5946	0.0	1.0	
3881	0.0	0.0	
2389	0.0	1.0	
3676	0.0	0.0	
...	
905	0.0	1.0	
5192	1.0	0.0	
3980	0.0	1.0	
235	0.0	0.0	
5157	0.0	1.0	

	Contract_One year	Contract_Two year	PaperlessBilling_Yes \
1814	0.0	1.0	0.0
5946	1.0	0.0	0.0
3881	0.0	1.0	0.0
2389	1.0	0.0	0.0
3676	1.0	0.0	0.0
...
905	0.0	0.0	1.0
5192	0.0	1.0	0.0
3980	0.0	0.0	1.0
235	0.0	0.0	1.0
5157	0.0	1.0	0.0

	PaymentMethod_Credit card (automatic)	PaymentMethod_Electronic
check \		
1814	0.0	
0.0		
5946	1.0	
0.0		
3881	0.0	
0.0		
2389	0.0	
1.0		
3676	0.0	
1.0		
...	...	
...		
905	0.0	
1.0		
5192	0.0	
0.0		
3980	0.0	
1.0		
235	0.0	
0.0		
5157	0.0	
0.0		

	PaymentMethod_Mailed check
1814	1.0
5946	0.0
3881	0.0
2389	0.0
3676	0.0
...	...
905	0.0
5192	1.0
3980	0.0
235	1.0

5157	0.0				
[5634 rows x 30 columns]					
	SeniorCitizen	tenure	MonthlyCharges	TotalCharges	gender_Male
\					
3381	0.0	41.0	79.85	3320.75	0.0
6180	1.0	66.0	102.40	6471.85	0.0
4829	0.0	12.0	45.00	524.35	0.0
3737	0.0	5.0	50.60	249.95	0.0
4249	0.0	10.0	65.90	660.05	0.0
...
2563	1.0	25.0	105.95	2655.25	1.0
2028	0.0	15.0	19.60	331.60	0.0
2899	0.0	71.0	53.95	3888.65	1.0
3474	1.0	65.0	85.75	5688.45	1.0
5154	0.0	17.0	104.20	1743.50	0.0
	Partner_Yes	Dependents_Yes	PhoneService_Yes	\	
3381	0.0	0.0	1.0		
6180	0.0	0.0	1.0		
4829	0.0	0.0	1.0		
3737	0.0	0.0	1.0		
4249	1.0	1.0	1.0		
...		
2563	0.0	0.0	1.0		
2028	0.0	0.0	1.0		
2899	0.0	0.0	0.0		
3474	1.0	1.0	1.0		
5154	1.0	1.0	1.0		
	MultipleLines_No phone service	MultipleLines_Yes	...	\	
3381		0.0	0.0	...	
6180		0.0	1.0	...	
4829		0.0	0.0	...	
3737		0.0	1.0	...	
4249		0.0	0.0	...	
...		
2563		0.0	1.0	...	
2028		0.0	0.0	...	
2899		1.0	0.0	...	

3474	0.0	1.0	...
5154	0.0	1.0	...

	StreamingTV_No internet service	StreamingTV_Yes \
3381	0.0	1.0
6180	0.0	1.0
4829	0.0	0.0
3737	0.0	0.0
4249	0.0	0.0
...
2563	0.0	1.0
2028	1.0	0.0
2899	0.0	1.0
3474	0.0	0.0
5154	0.0	1.0

	StreamingMovies_No internet service	StreamingMovies_Yes \
3381	0.0	1.0
6180	0.0	1.0
4829	0.0	0.0
3737	0.0	0.0
4249	0.0	1.0
...
2563	0.0	1.0
2028	1.0	0.0
2899	0.0	0.0
3474	0.0	0.0
5154	0.0	1.0

	Contract_One year	Contract_Two year	PaperlessBilling_Yes \
3381	1.0	0.0	1.0
6180	0.0	1.0	1.0
4829	0.0	0.0	1.0
3737	0.0	0.0	1.0
4249	1.0	0.0	1.0
...
2563	0.0	0.0	0.0
2028	0.0	1.0	0.0
2899	0.0	1.0	0.0
3474	0.0	0.0	1.0
5154	0.0	0.0	1.0

	PaymentMethod_Credit card (automatic) check \	PaymentMethod_Electronic
3381		0.0
0.0		
6180		0.0
0.0		
4829		0.0
0.0		

3737	0.0
0.0	
4249	0.0
0.0	
...	...
...	
2563	0.0
0.0	
2028	0.0
0.0	
2899	0.0
0.0	
3474	0.0
1.0	
5154	0.0
1.0	

	PaymentMethod_Mailed check
3381	0.0
6180	0.0
4829	0.0
3737	1.0
4249	1.0
...	...
2563	1.0
2028	1.0
2899	0.0
3474	0.0
5154	0.0

[1409 rows x 30 columns]

1814	0.0
5946	1.0
3881	0.0
2389	0.0
3676	0.0

...	
905	1.0
5192	0.0
3980	1.0
235	1.0
5157	0.0

Name: Churn, Length: 5634, dtype: float64

3381	0.0
6180	0.0
4829	0.0
3737	1.0
4249	0.0

...

```

2563      1.0
2028      0.0
2899      0.0
3474      0.0
5154      1.0
Name: Churn, Length: 1409, dtype: float64

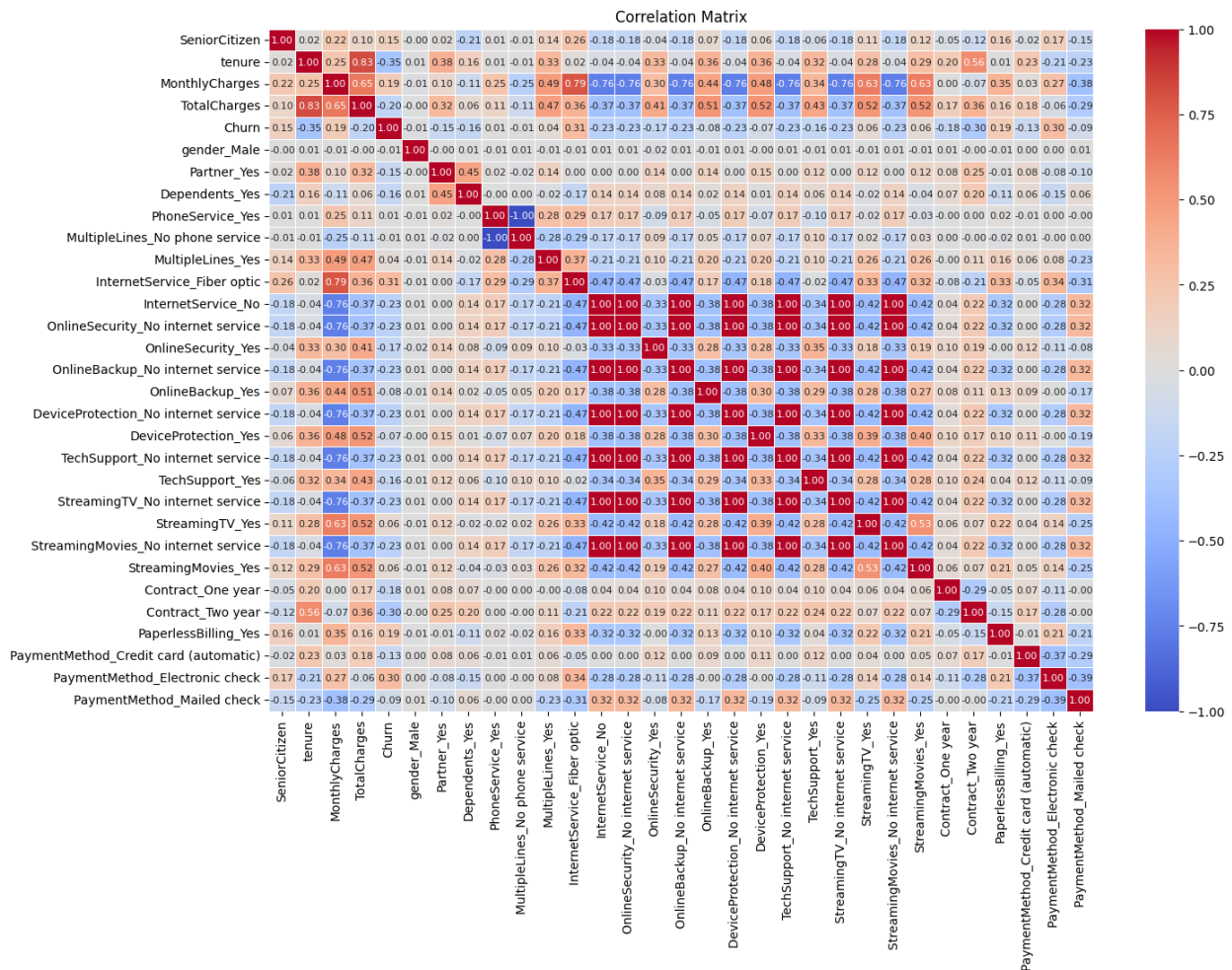
```

Task 3 - Feature Selection

```

#Correlation_Matrix
import matplotlib.pyplot as plt
import seaborn as sns
correlation_matrix = telco.corr()
plt.figure(figsize=(15,10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
            annot_kws={'size':8}, fmt = '.2f', linewidths=.5)
plt.title('Correlation Matrix')
plt.show()

```



In here we have got Contract_Two year (-0.30) Customers on 2-year contracts are less likely to churn.

Contract_One year (-0.20) Similar effect but less strong.

tenure (-0.35) Higher tenure = more loyal = lower churn.

OnlineSecurity_Yes (-0.28) Customers with online security are less likely to leave.

TechSupport_Yes (-0.27) Support availability reduces churn.

MonthlyCharges (+0.19) Slightly higher charges → more churn (but weak).

```
Selected_features = ['Contract_Two year', 'Contract_One year',  
'tenure', 'OnlineSecurity_Yes', 'TechSupport_Yes', 'MonthlyCharges']  
X = telco[Selected_features]  
y = telco['Churn']  
  
from sklearn.model_selection import train_test_split  
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size =  
0.2, random_state = 0)  
  
from sklearn.preprocessing import StandardScaler  
sc = StandardScaler()  
X_train = sc.fit_transform(X_train)  
X_test = sc.transform(X_test)
```

Task 4 - Model Selection

- **Logistic Regression:** Chosen for interpretability and suitability for binary classification with scaled features.
- **Decision Tree:** Selected to capture non-linear relationships in features like **tenure** and **Contract**.
- **Random Forest:** Used for robustness and handling categorical features post one-hot encoding.
- **Gradient Boosting:** Included for improved performance on imbalanced data.

Task 5:- Model Training

#Logistic Regression

```
from sklearn.linear_model import LogisticRegression  
Classifier = LogisticRegression(random_state = 0)  
Classifier.fit(X_train, y_train)  
  
LogisticRegression(random_state=0)  
LogisticRegression(random_state=0)
```

```

y_pred = Classifier.predict(X_test)
y_pred_proba = Classifier.predict_proba(X_test)  # Predicted
probabilities

#Decision Tress
from sklearn.tree import DecisionTreeClassifier
Classifier = DecisionTreeClassifier(criterion = 'entropy',
random_state = 0)
Classifier.fit(X_train, y_train)

DecisionTreeClassifier(criterion='entropy', random_state=0)

#Random Forest
from sklearn.ensemble import RandomForestClassifier
Classifier = RandomForestClassifier(n_estimators = 10, criterion =
'entropy', random_state = 0)
Classifier.fit(X_train, y_train)

RandomForestClassifier(criterion='entropy', n_estimators=10,
random_state=0)

from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report

# Train GB model
gb_model = GradientBoostingClassifier(random_state=0)
gb_model.fit(X_train, y_train)

GradientBoostingClassifier(random_state=0)

```

TASK 6 :- MODEL EVALUATION

```

#Logistic Regression

from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix, roc_auc_score
auc_score = roc_auc_score(y_test, y_pred_proba[:, 1])

print("Accuracy:", accuracy_score(y_test, y_pred))

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

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

print("AUC Score:\n", auc_score)

Accuracy: 0.7906316536550745
Confusion Matrix:

```

```

[[933 108]
 [187 181]]
Classification Report:

```

	precision	recall	f1-score	support
0.0	0.83	0.90	0.86	1041
1.0	0.63	0.49	0.55	368
accuracy			0.79	1409
macro avg	0.73	0.69	0.71	1409
weighted avg	0.78	0.79	0.78	1409

```

AUC Score:
0.8181958192373554

```

#Decision Tree

```

from sklearn.tree import DecisionTreeClassifier

dt_classifier = DecisionTreeClassifier(criterion = 'entropy',
random_state = 0)
dt_classifier.fit(X_train, y_train)

dt_y_pred = dt_classifier.predict(X_test)
dt_y_pred_proba = dt_classifier.predict_proba(X_test)
auc_score_dt = roc_auc_score(y_test, dt_y_pred_proba[:, 1])
print("Decision Tree - Accuracy:", accuracy_score(y_test, dt_y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, dt_y_pred))
print("Classification Report:\n", classification_report(y_test,
dt_y_pred))
print("Decision Tree AUC Score:", auc_score_dt)

```

```

Decision Tree - Accuracy: 0.716820440028389
Confusion Matrix:
[[858 183]
 [216 152]]
Classification Report:

```

	precision	recall	f1-score	support
0.0	0.80	0.82	0.81	1041
1.0	0.45	0.41	0.43	368
accuracy			0.72	1409
macro avg	0.63	0.62	0.62	1409
weighted avg	0.71	0.72	0.71	1409

```

Decision Tree AUC Score: 0.6308185064528254

```

#Random Forest

```

from sklearn.ensemble import RandomForestClassifier
rf_classifier = RandomForestClassifier(n_estimators = 10, criterion =

```

```
'entropy', random_state = 0) # Initialize rf_classifier
rf_classifier.fit(X_train, y_train)

rf_y_pred = rf_classifier.predict(X_test)
rf_y_pred_proba = rf_classifier.predict_proba(X_test)
auc_score_rf = roc_auc_score(y_test, rf_y_pred_proba[:, 1])
print("Random Forest - Accuracy:", accuracy_score(y_test, rf_y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, rf_y_pred))
print("Classification Report:\n", classification_report(y_test,
rf_y_pred))
print("Random Forest AUC Score:", auc_score_rf)
```

Random Forest - Accuracy: 0.752306600425834

Confusion Matrix:

```
[[897 144]
```

```
[205 163]]
```

Classification Report:

	precision	recall	f1-score	support
0.0	0.81	0.86	0.84	1041
1.0	0.53	0.44	0.48	368
accuracy			0.75	1409
macro avg	0.67	0.65	0.66	1409
weighted avg	0.74	0.75	0.74	1409

Random Forest AUC Score: 0.7611710625234933

#Gradient Boost

```
y_pred_gb = gb_model.predict(X_test)
y_pred_gb_proba = gb_model.predict_proba(X_test) # Predicted
probabilities
```

```
print("Gradient Boosting Classifier:")
print("Accuracy:", accuracy_score(y_test, y_pred_gb))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_gb))
print("Classification Report:\n", classification_report(y_test,
y_pred_gb))
auc_score_gb = roc_auc_score(y_test, y_pred_gb_proba[:, 1])
print("Gradient Boosting AUC Score:", auc_score_gb)
```

Gradient Boosting Classifier:

Accuracy: 0.7849538679914834

Confusion Matrix:

```
[[929 112]
```

```
[191 177]]
```

Classification Report:

	precision	recall	f1-score	support
--	-----------	--------	----------	---------

	0.0	0.83	0.89	0.86	1041
	1.0	0.61	0.48	0.54	368
accuracy				0.78	1409
macro avg		0.72	0.69	0.70	1409
weighted avg		0.77	0.78	0.78	1409
Gradient Boosting AUC Score: 0.8254213131186567					

The Summary Table for all evaluation of algorithms used in this .

Model Evaluation Summary

Model	Accuracy	Class 1 Recall	Class 1 Precision	F1 (Class 1)	ROC-AUC
Logistic Regression	0.791	0.49	0.63	0.55	0.818
Decision Tree	0.717	0.41	0.45	0.43	0.631
Random Forest	0.752	0.44	0.53	0.48	0.761
Gradient Boosting	0.785	0.48	0.61	0.54	0.825

Model Evaluation Insights

Logistic Regression (0.791 accuracy, 0.818 ROC-AUC) and Gradient Boosting (0.785 accuracy, 0.825 ROC-AUC) lead, but low Class 1 recall (0.49, 0.48) shows difficulty predicting churners due to class imbalance (~26% churn). Decision Tree (0.717 accuracy, 0.631 ROC-AUC) overfits. Random Forest (0.752 accuracy, 0.761 ROC-AUC) is moderate. SMOTE could improve recall.
Thank You