Predictive Analysis for Bank Telemarketing Success

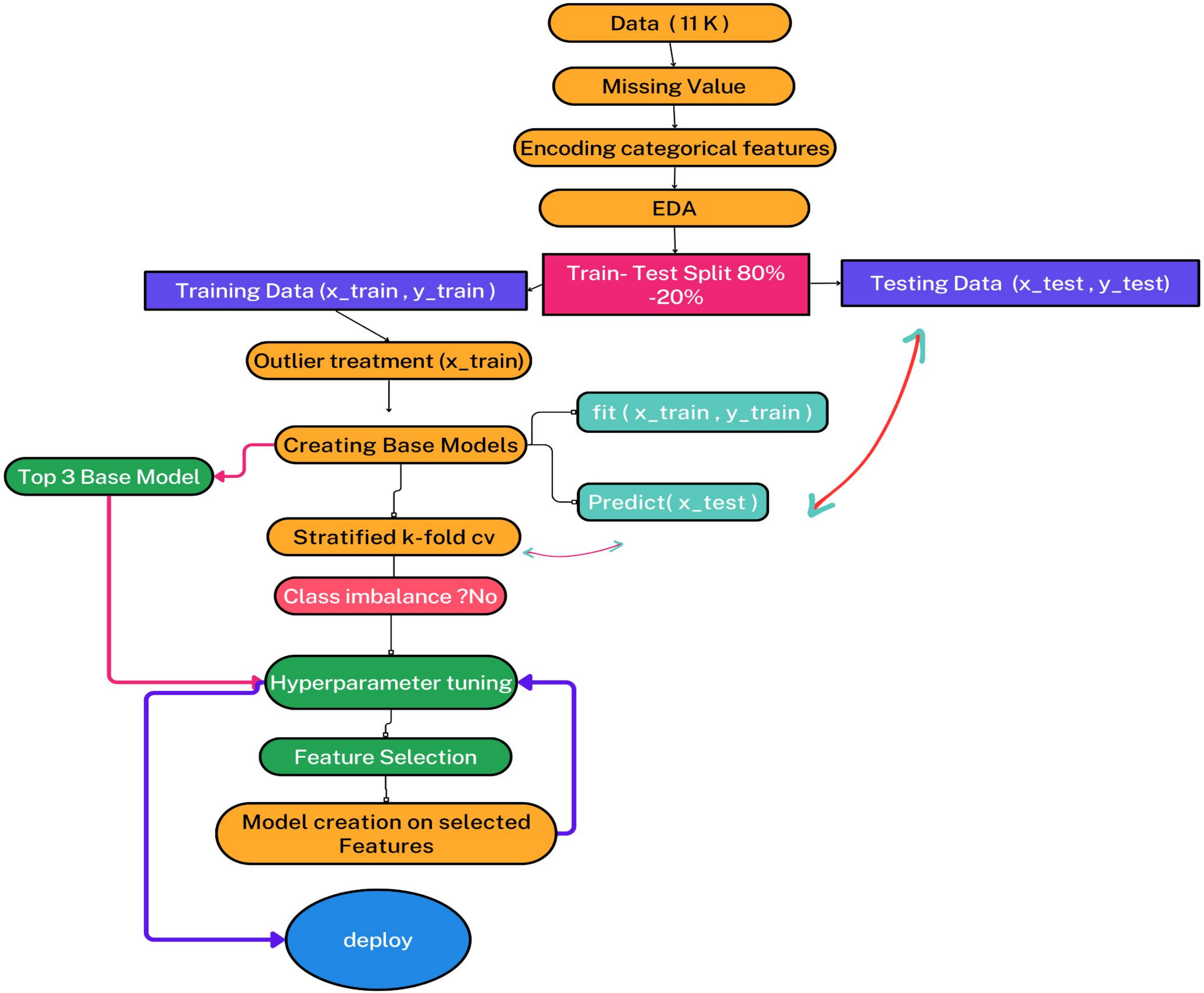
Contents

02 Flowchart

Problem Statement

Campaign Success Prediction:
Building a Predictive Model to Determine Customer Subscription to Term Deposit Policy

Project Flowchart



Dataset Information

Dataset Shape - (11162, 17)

Dataset format - CSV File

Target Feature - Deposit (yes , no)

Independent Features -

Age,job,marital,education,default,balance,housing,loan,contact,day
,month,duration,campaign,pdays,previous,poutcome

Data Analysis (EDA)

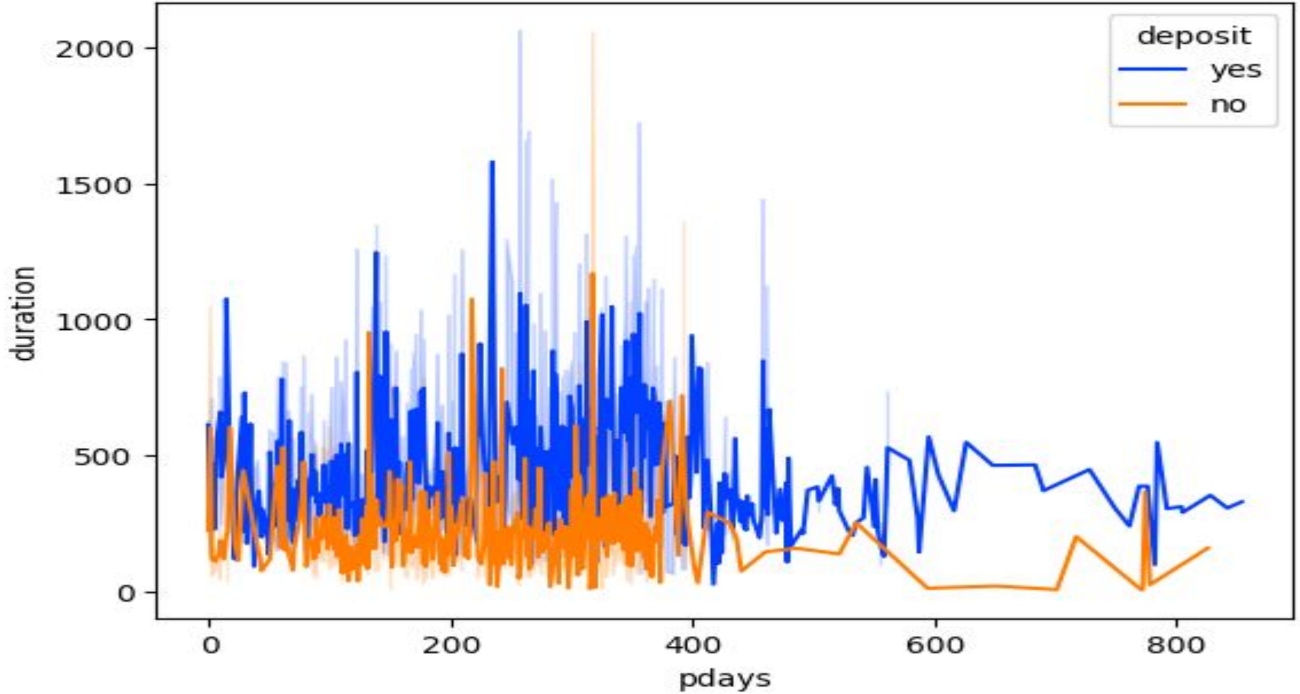
1. No Class Imbalance

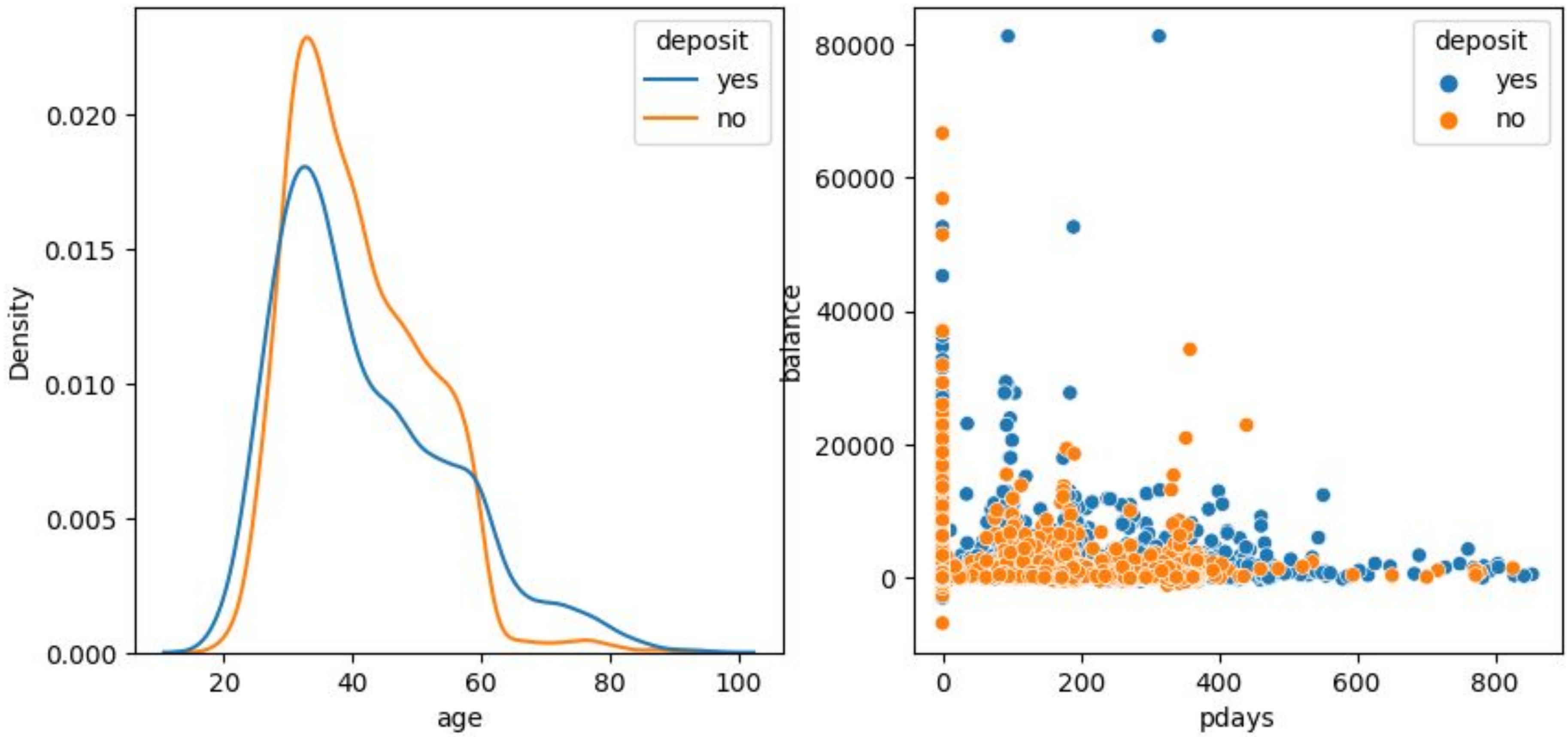
2. Positive correlation between call duration and subscription likelihood.

3.Impact of Categorical Columns on the Target Variable:
Single Marital Status, tertiary education, and do not have an existing housing loan. These demographic factors appear to influence the subscription rate positively.

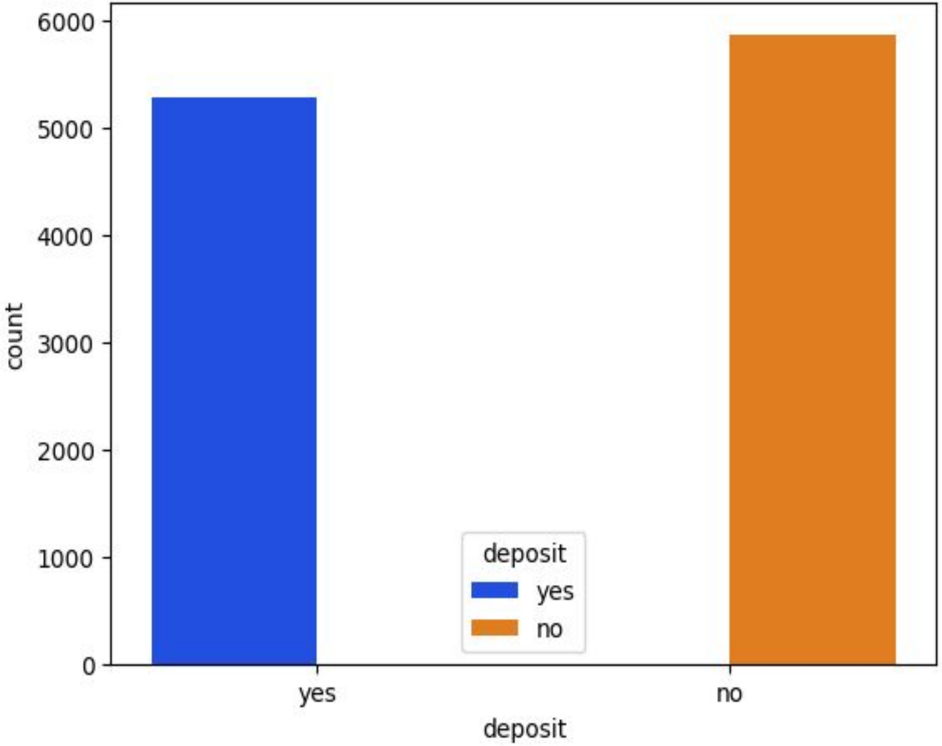
5.Effect of Last Contact Month on Subscription:
The count of customers subscribing to a term deposit is notably higher when they were last contacted in the months of February, March, April, and September.

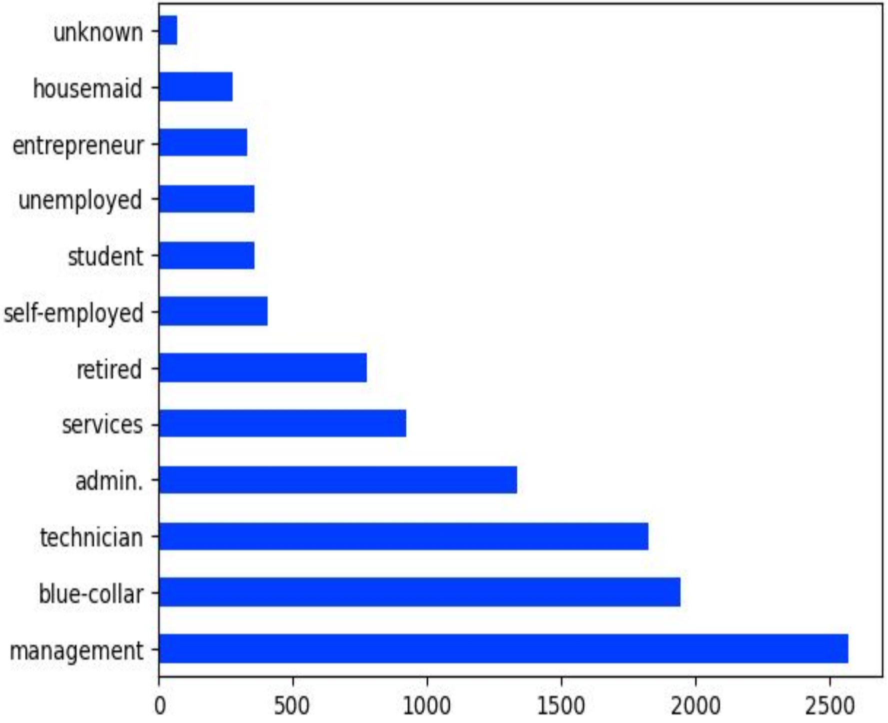
	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	deposit
7567	37	admin.	married	secondary	no	641	yes	no	unknown	5	jun	42	1	-1	0	unknown	no
6780	30	services	single	secondary	no	-100	yes	yes	cellular	15	may	292	1	-1	0	unknown	no
5220	61	retired	married	tertiary	no	3140	yes	yes	cellular	6	aug	975	4	98	1	unknown	yes

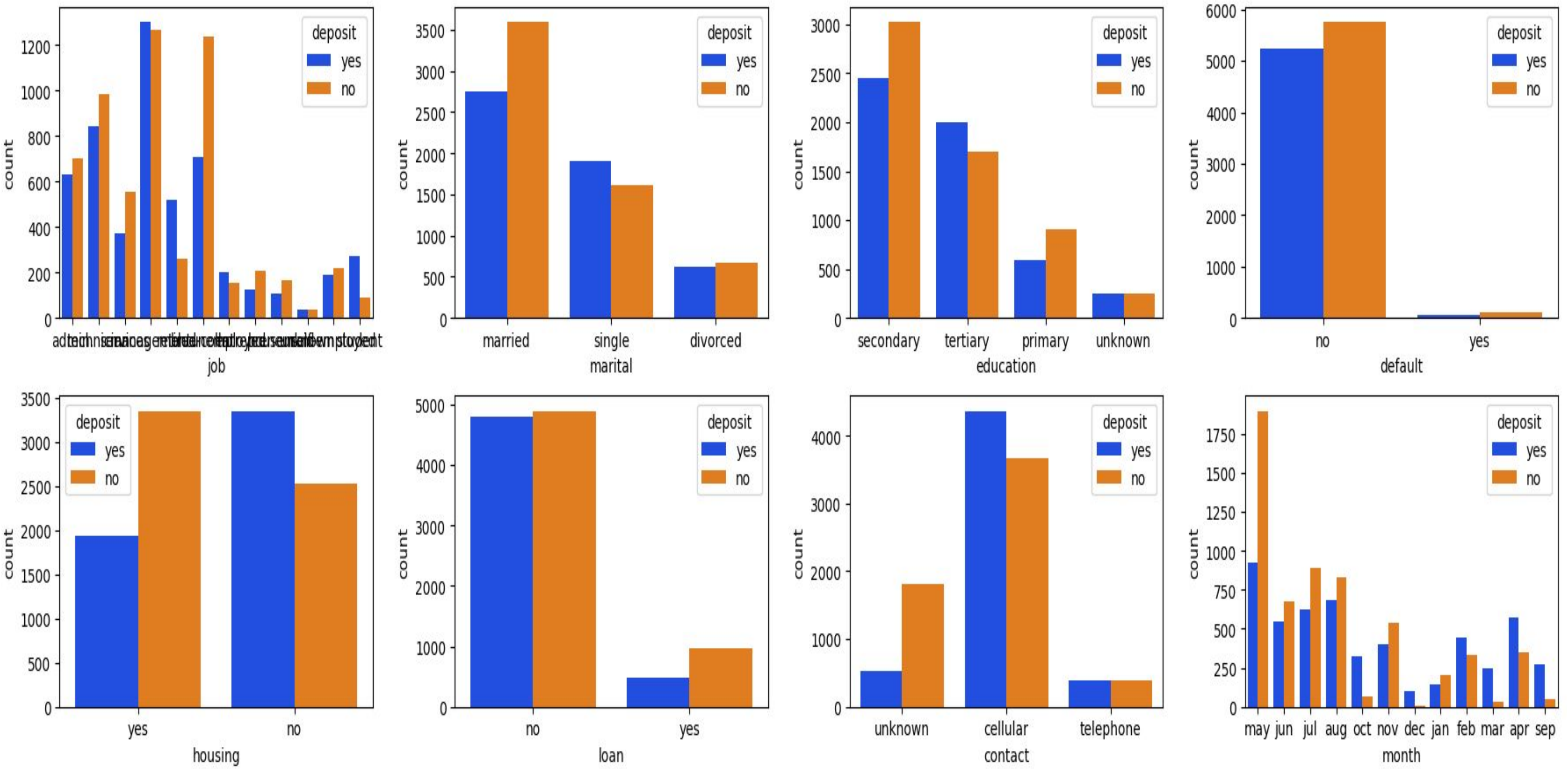




deposit
yes
no
Density
0.000
0.005
0.010
0.015
0.020
20
40
60
80
100
age
deposit
yes
no
balance
0
20000
40000
60000
80000
0
200
400
600
800
pdays


6000
5000
4000
3000
2000
1000
0
count
yes
no
deposit
deposit
yes
no


unknown
housemaid
entrepreneur
unemployed
student
self-employed
retired
services
admin.
technician
blue-collar
management
0
500
1000
1500
2000
2500


count
0
200
400
600
800
1000
1200
deposit
yes
no
job
count
0
500
1000
1500
2000
2500
3000
3500
deposit
yes
no
married
single
divorced
marital
count
0
500
1000
1500
2000
2500
3000
deposit
yes
no
secondary
tertiary
primary
unknown
education
count
0
1000
2000
3000
4000
5000
6000
deposit
yes
no
no
yes
default
count
0
500
1000
1500
2000
2500
3000
3500
deposit
yes
no
yes
no
housing
count
0
1000
2000
3000
4000
5000
deposit
yes
no
no
yes
loan
count
0
1000
2000
3000
4000
deposit
yes
no
unknown
cellular
telephone
contact
count
0
250
500
750
1000
1250
1500
1750
deposit
yes
no
may
jun
jul
aug
oct
nov
dec
jan
feb
mar
apr
sep
month

Data Cleaning and Preprocessing

1. Special Codes Handling:

Pdays Adjustment: Replaced -1 with 0 for uniform representation of non-contacted clients.

2. Managing Missing Values:

Filled 'job', 'education', 'contact' having NaNs present as 'unknown' in data
Dropped 'poutcome' Column: More than 50% missing records

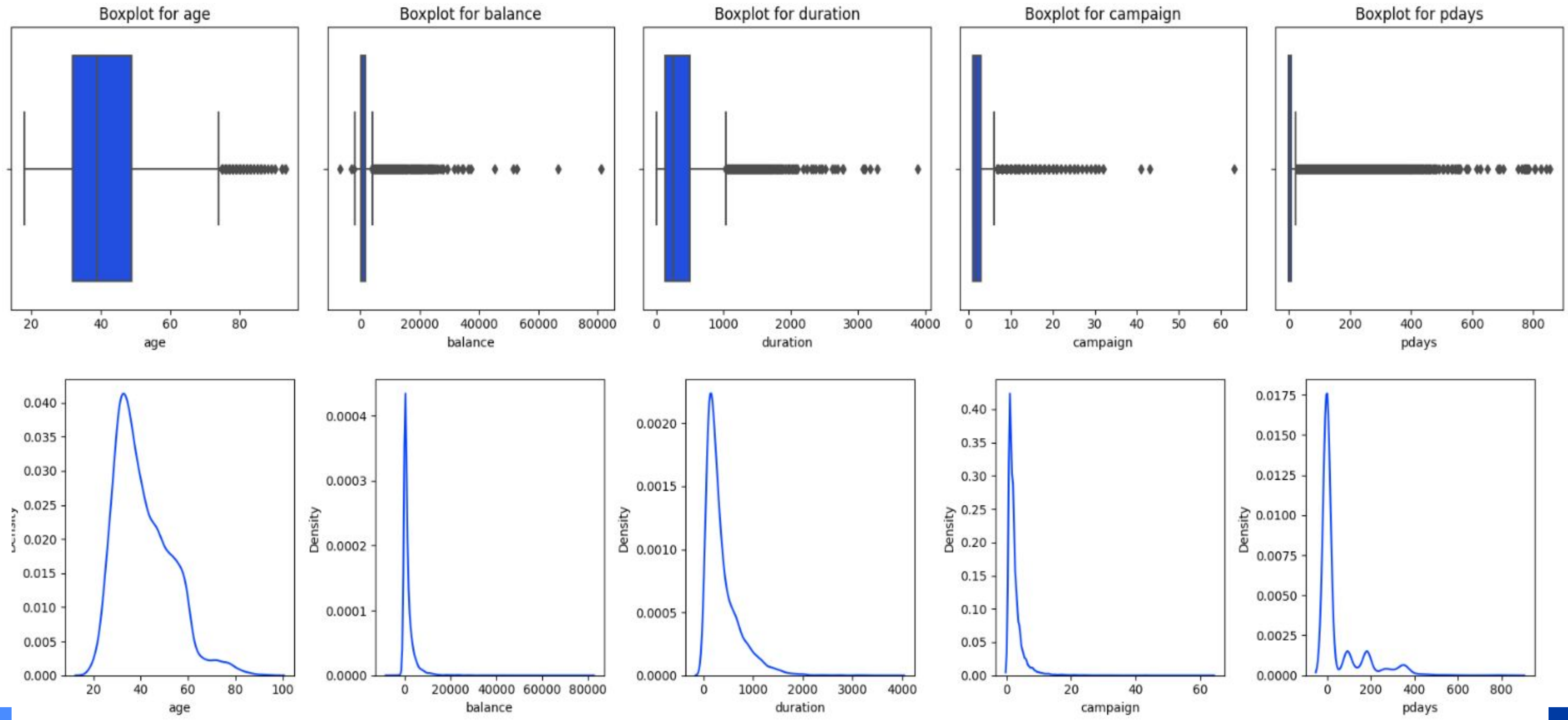
3. Missing Value Imputation:

Strategy: Used SimpleImputer replaced missing values with most frequent values.

4. Categorical to Numeric Conversion:

Label Encoding(LabelEncoder): Transformed categorical features into numeric values for analysis.

Outlier Detection



Base Models Performance Evaluation

	Model	Accuracy	Precision	Recall	F1 Score	AUC	Specificity	PRC score
0	log	75.279893	0.724138	0.793548	0.757256	0.753917	0.714286	0.674952
1	SVC	69.726825	0.702676	0.653456	0.677173	0.696066	0.738676	0.627551
2	KNN	72.637707	0.714286	0.728111	0.721132	0.726425	0.724739	0.652188
3	Random Forest	82.489924	0.807080	0.840553	0.823476	0.825329	0.810105	0.755867
4	adaboost	79.892521	0.798311	0.784332	0.791260	0.798525	0.812718	0.730933
5	Gradient Boosting	82.400358	0.808929	0.835023	0.821769	0.824306	0.813589	0.755635
6	catBoost	84.773847	0.826468	0.869124	0.847260	0.848325	0.827526	0.781895
7	XGBoost	83.161666	0.814552	0.846083	0.830018	0.832014	0.817944	0.763966
8	Decision Tree	76.175549	0.760603	0.743779	0.752097	0.761262	0.778746	0.690217

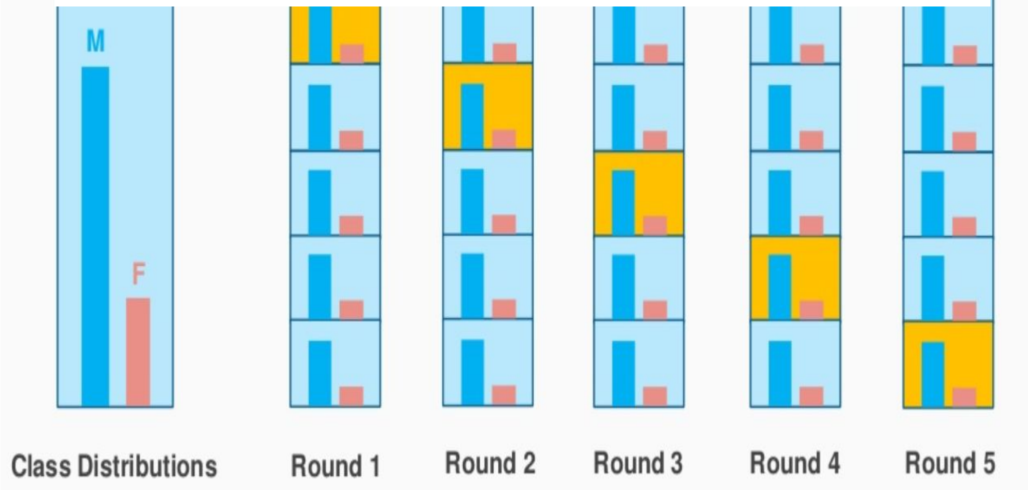
Stratified K- fold Cross Validation Results

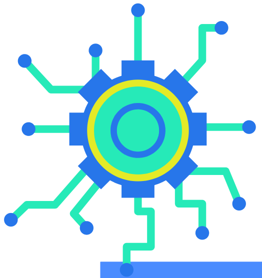
CatBoostClassifier (cross validation results)

- on testing data => 84.77
- on training data (cross validation) => 85.32

XGBClassifier (cross validation results)

- on testing data => 83.16
- on training data (cross validation) => 84.18





Hyperparameter tuning on Top 3 base models

RandomSearchCv

Finding Best Hyperparametrs → **Feature selection** → **Selecting Best Model**

- Done Hyperparameter tuning for =>
- **CatBoostClassifier**
- **XGBClassifier**
- **RandomForestClassifier**

- Selected features using **feature_impotances_** attribute of models
- Generated models on their selected features

- "Evaluated model performance; **CatBoostClassifier** emerged as the top performer based on selected features."

Feature selection - Recursive Feature Elimination

```
from sklearn.feature_selection import RFE
selector = RFE(CatBoostClassifier(verbose=False), n_features_to_select=7, step=1)
selector.fit(x_train,y_train)
```

```
Selected Features: ['age', 'balance', 'housing', 'day', 'month', 'duration', 'pdays']
```

Feature_Score_cat	columns_cat	Feature_Score_xgb2	columns_xgb	Feature_Score_rf2	columns_rf
33.414440	duration	0.277740	pdays	0.447330	duration
19.184392	month	0.171153	duration	0.090855	month
10.767175	day	0.147272	housing	0.081055	age
5.716065	age	0.092132	month	0.074622	balance
5.343753	housing	0.057053	loan	0.064487	day
5.073916	pdays	0.038255	previous	0.045662	housing
4.224723	balance	0.034531	day	0.043628	previous
4.158954	job	0.030671	age	0.038503	pdays
2.787719	education	0.027352	education	0.032323	job
2.670489	previous	0.026517	contact	0.030191	campaign
2.292366	campaign	0.026381	campaign	0.017447	education
2.069355	marital	0.026284	balance	0.016666	marital
1.540071	loan	0.023796	marital	0.011808	loan
0.648264	contact	0.020865	job	0.004521	contact
0.108317	default	0.000000	default	0.000901	default

```
x_train1=x_train[['duration','housing', 'age', 'day', 'month','balance', 'pdays']]
x_test1=x_test[['duration','housing', 'age', 'day', 'month','balance', 'pdays']]
```

Procedure on New Train -Test set

01

Training and Testing

Trained the top 3 performing models on new independent features

02

ROC-AUC , PRC Curve

Plot a beautiful ROC-AUC And PRC CURVE. Finding **Optimal threshold value** => **got 0.46**

03

Evaluate model using threshold

Best Performer is CatBoostClassifier

04

Cross Validation

Getting perfect model

05

Deploy

Evaluation on New Train & test

CatBoostClassifier

```
Accuracy:   85.53515450067174
f1 score :   0.8553515450067174
roc_score :   0.85603293244914
prc_score :   0.790426735771544
Precision: 0.8318815331010453
Recall: 0.880184331797235
specificity :   0.8318815331010
Confusion Matrix:
[[955 193]
 [130 955]]
```

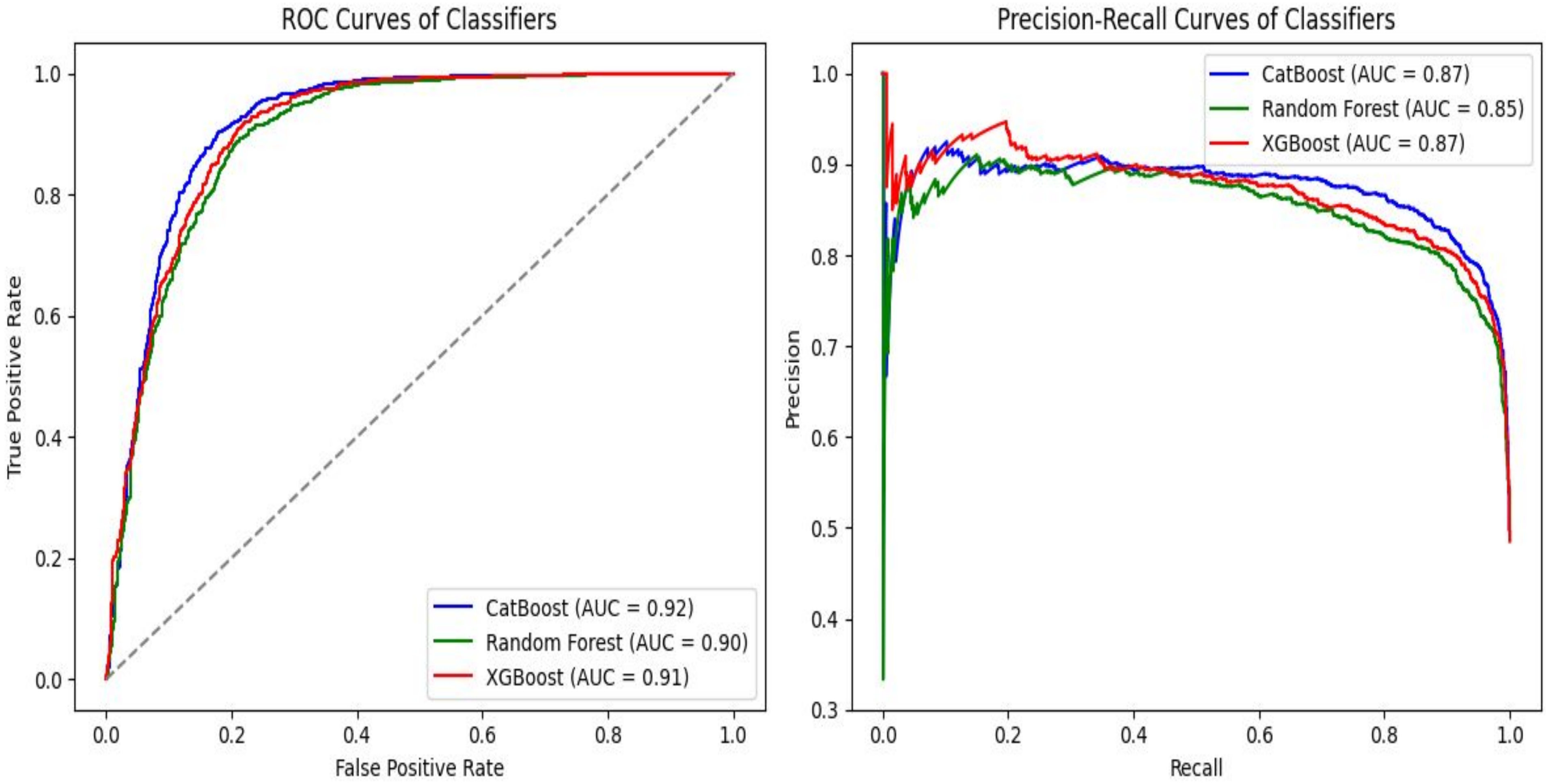
XGBClassifier

```
Accuracy:   83.69905956112854
f1 score :   0.8354430379746834
roc_score :   0.8373918174665618
prc_score :   0.7703171037020241
Precision: 0.8198757763975155
Recall: 0.8516129032258064
specificity :   0.82317073170731
Confusion Matrix:
[[945 203]
 [161 924]]
```

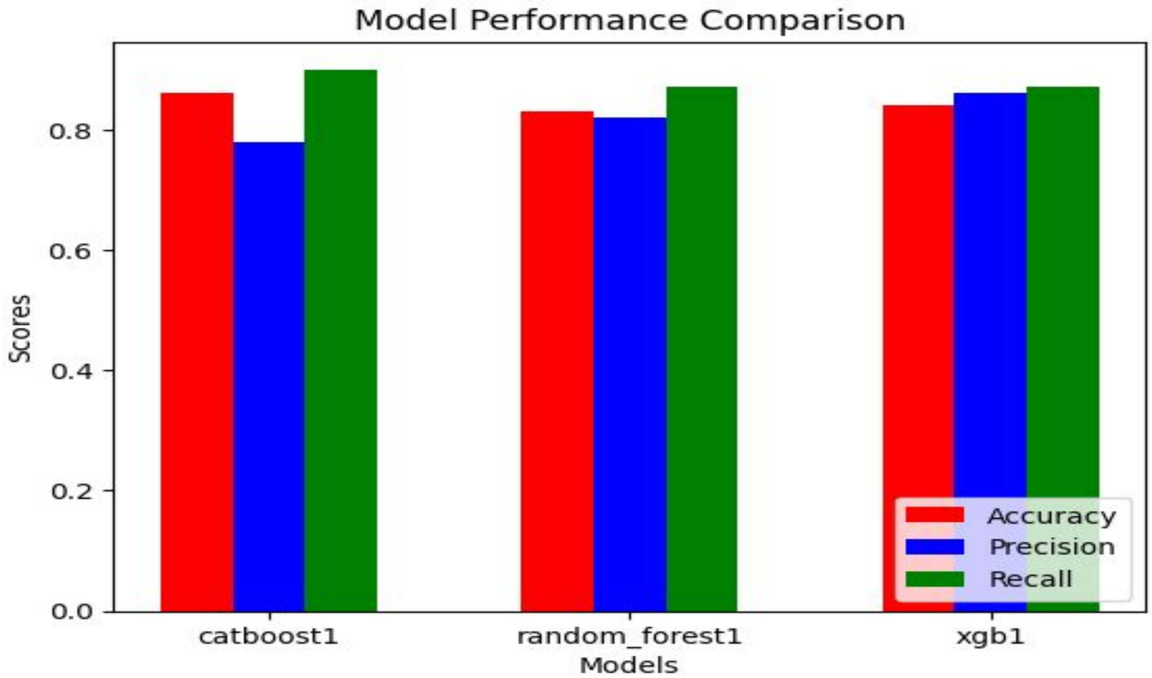
RandomForestClassifier

```
Accuracy:   82.75862068965517
f1 score :   0.8263419034731619
roc_score :   0.828043160615938
prc_score :   0.7588309079852491
Precision: 0.8091872791519434
Recall: 0.8442396313364056
specificity :   0.8118466898954704
Confusion Matrix:
[[932 216]
 [169 916]]
```

	Model	Accuracy	Precision	Recall	F1 Score	AUC	Specificity
0	Random Forest	83.79	0.81	0.87	0.84	0.84	0.80
1	catBoost	86.07	0.83	0.90	0.86	0.86	0.82
2	XGBoost	84.19	0.82	0.87	0.84	0.84	0.82


ROC Curves of Classifiers
True Positive Rate
False Positive Rate
CatBoost (AUC = 0.92)
Random Forest (AUC = 0.90)
XGBoost (AUC = 0.91)
Precision-Recall Curves of Classifiers
Precision
Recall
CatBoost (AUC = 0.87)
Random Forest (AUC = 0.85)
XGBoost (AUC = 0.87)

Evaluation on New Train & test



	Model	Accuracy	Precision	Recall	F1 Score	AUC	Specificity
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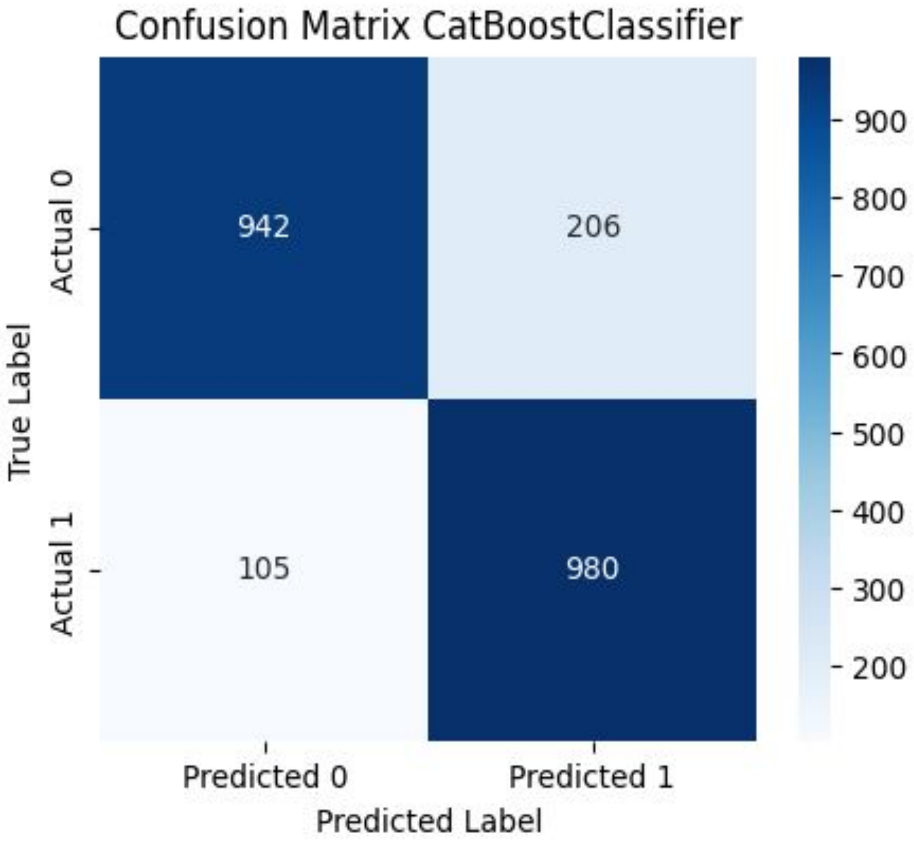
1	catBoost	86.07	0.83	0.90	0.86	0.86	0.82
2	XGBoost	84.19	0.82	0.87	0.84	0.84	0.82

Final Result




```
Accuracy:  86.07254814151366
f1 score :  0.863055922501109
roc_score :  0.8618916488704058
prc_score :  0.793363672344815
Precision: 0.8263069139966274
Recall: 0.9032258064516129
specificity :  0.8205574912891986
Confusion Matrix:
[[942 206]
 [105 980]]
              precision    recall  f1-score   support

           0       0.90      0.82      0.86      1148
           1       0.83      0.90      0.86      1085

    accuracy                           0.86      2233
   macro avg       0.86      0.86      0.86      2233
weighted avg       0.86      0.86      0.86      2233
```

Conclusion and Future Enhancement

1. The following variables seem to be the most relevant inputs in predicting the Success rate of bank direct marketing campaign
   - **Duration - call duration**
   - **Pdays - Number of days since last contact**
   - **Month - month of contact**
   - **Age - customer age**
   - **housing - weather customer having housing loan.**
2. A client is more likely to subscribe term deposit if customer talks for more duration. Campaign is more likely to be successful during March, September, December (end of every trimester).

3. **An essential future enhancement** for our project involves **deploying the trained machine learning model** into real-world applications
4. "Incorporating **advanced ensemble techniques, such as stacking and voting,** will enhance our model's accuracy and robustness, serving as a key future enhancement."

Demerits

1. The absence of **‘advanced ensemble techniques’** such as **stacking and voting** in the current implementation suggests a possibility for increased accuracy.

Thanks