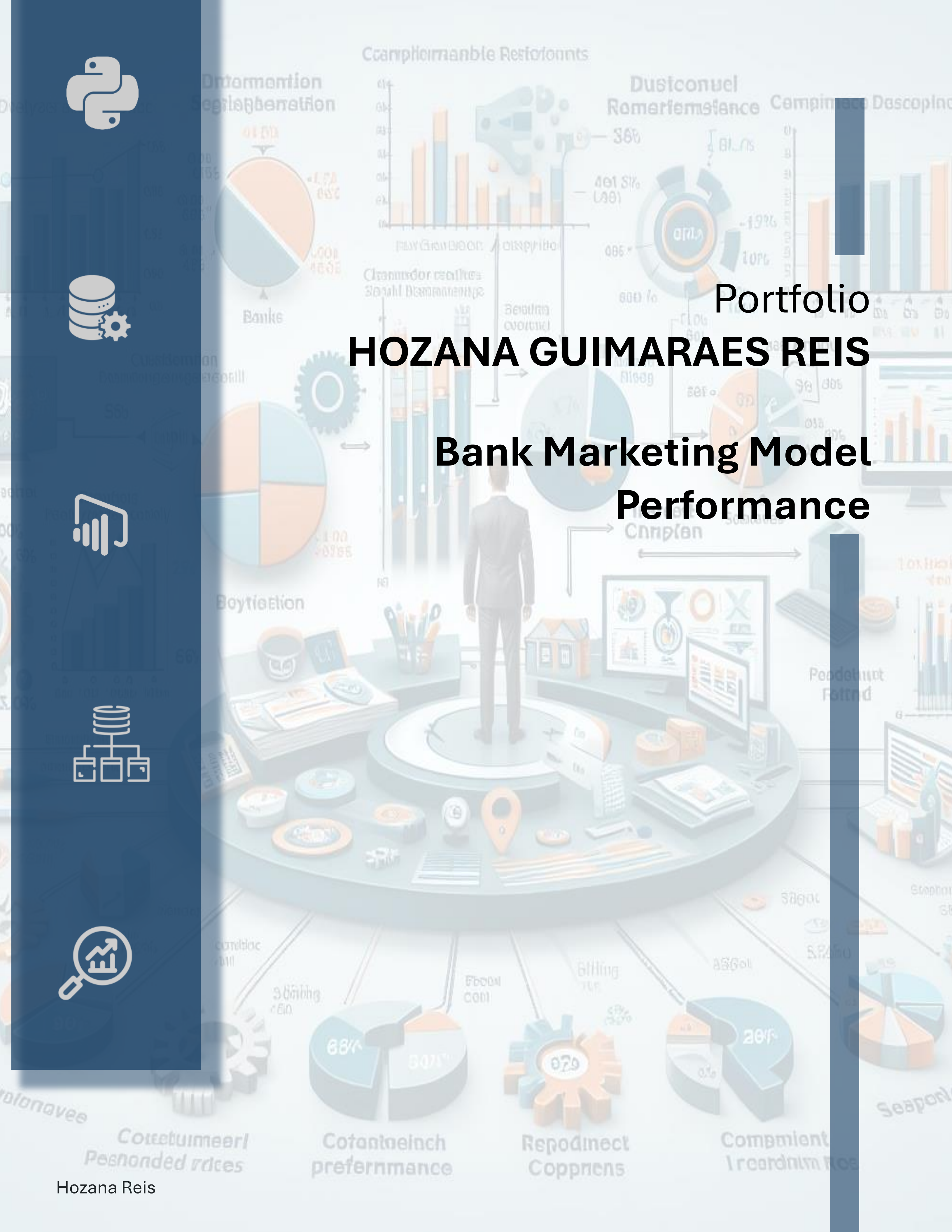


Portfolio

HOZANA GUIMARAES REIS

Bank Marketing Model Performance

Hozana Reis

Table of Contents

1. Objective

The objective is to use all the information to predict whether someone will end up saving money with the bank. This helps the bank decide who to focus on when they're trying to get people to save money with them. The Analysis will come across 7 classifiers and each performance for better decision-making. Additionally, the feature importance of various factors will be examined to gain insights into the key drivers influencing the predicted outcomes.

Technologies Used:

Programming Language: Python

Data Analysis: Pandas, NumPy

Machine Learning: Scikit-learn.

Visualization: Matplotlib, Seaborn

Business Intelligence: Power BI

Classifiers: Logistic Regression, Decision Tree, Gradient Boosting, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Naive Bayes

2. Libraries

2.1 Importing Necessary Libraries.

```
# Libraries used
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder,StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score, recall_score, f1_score
```

✓ 0.0s Python

Note: More Libraries will be used, they are placed along with the code

3. Exploratory Data Analysis (EDA)

3.1 Load the Data

```
df = pd.read_csv("bank-additional-full.csv", delimiter=';')
print(df.head(5))
```

✓ 0.2s Python

```
   age        job  marital    education  default housing loan    contact  \
0   56  housemaid  married     basic.4y       no      no   no  telephone
1   57   services  married  high.school  unknown      no   no  telephone
2   37   services  married  high.school       no     yes   no  telephone
3   40     admin.  married     basic.6y       no      no   no  telephone
4   56   services  married  high.school       no      no  yes  telephone

  month day_of_week  ...  campaign  pdays  previous     poutcome emp.var.rate  \
0   may         mon  ...         1    999         0  nonexistent          1.1
1   may         mon  ...         1    999         0  nonexistent          1.1
2   may         mon  ...         1    999         0  nonexistent          1.1
3   may         mon  ...         1    999         0  nonexistent          1.1
4   may         mon  ...         1    999         0  nonexistent          1.1

   cons.price.idx  cons.conf.idx  euribor3m  nr.employed   y
0          93.994          -36.4      4.857       5191.0  no
1          93.994          -36.4      4.857       5191.0  no
2          93.994          -36.4      4.857       5191.0  no
3          93.994          -36.4      4.857       5191.0  no
4          93.994          -36.4      4.857       5191.0  no

[5 rows x 21 columns]
```

3.2 Data Description and Missing Values Check

Column Name	Description
age	Age of the client.
job	Type of job the client has.
marital	Marital status of the client.
education	Level of education of the client.
default	Whether they've had trouble paying debts before. (yes, no, or unknown).
housing	Whether the client has housing loan (yes, no, or unknown).
loan	Whether they have other types of loans. (yes, no, or unknown).
contact	Contact communication type (telephone or cellular).
month	Last contact month of the year. When the bank contacted them.
day_of_week	Last contact day of the week. Which day of the week they were contacted.
duration	Last contact duration, in seconds.
campaign	How many times the bank has contacted them.
pdays	Number of days since the client was last contacted from a previous campaign (-1 means client was not previously contacted).
previous	How many times the bank contacted them before this campaign.
poutcome	Outcome of the previous marketing campaign.
emp.var.rate	How the employment situation is changing. (quarterly indicator).
cons.price.idx	How prices of goods and services are changing.(monthly indicator).
cons.conf.idx	How confident consumers are about the economy.(monthly indicator).
euribor3m	Euribor 3-month rate. A type of interest rate (daily indicator).
nr.employed	How many people are employed. (quarterly indicator).
y	Whether they ended up saving money with the bank or not.(yes or no).

```python
# checking missing values
df.isnull().sum()
```

✓ 0.0s Python

```
age               0
job               0
marital           0
education         0
default           0
housing           0
loan              0
contact           0
month             0
day_of_week       0
duration          0
campaign          0
pdays             0
previous          0
poutcome          0
emp.var.rate      0
cons.price.idx    0
cons.conf.idx     0
euribor3m         0
nr.employed       0
y                 0
dtype: int64
```

3.3 Data Information

```python
df.info()
```

✓ 0.2s Python

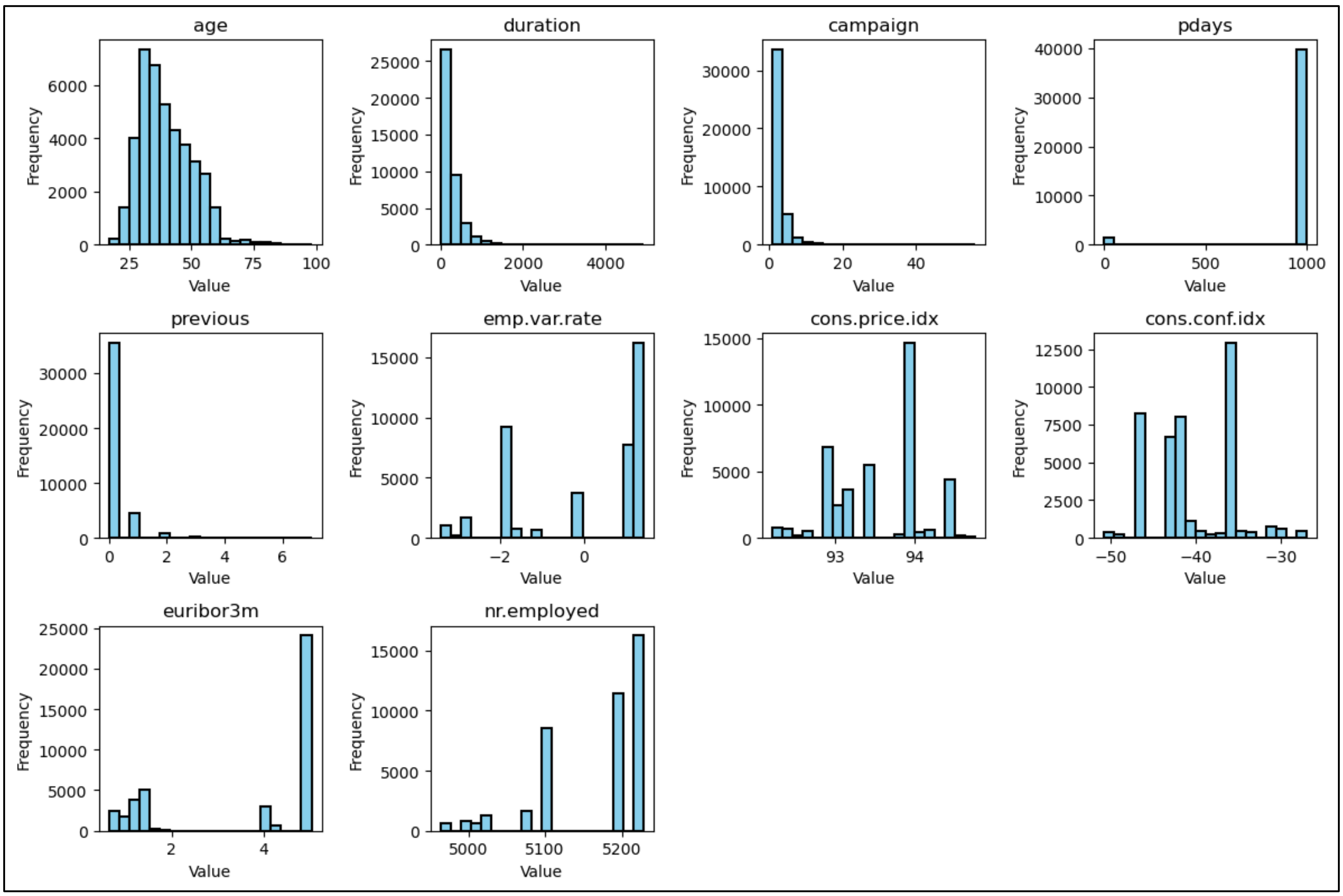
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   age             41188 non-null  int64  
 1   job             41188 non-null  object 
 2   marital         41188 non-null  object 
 3   education       41188 non-null  object 
 4   default         41188 non-null  object 
 5   housing         41188 non-null  object 
 6   loan            41188 non-null  object 
 7   contact         41188 non-null  object 
 8   month           41188 non-null  object 
 9   day_of_week     41188 non-null  object 
 10  duration        41188 non-null  int64  
 11  campaign        41188 non-null  int64  
 12  pdays           41188 non-null  int64  
 13  previous        41188 non-null  int64  
 14  poutcome        41188 non-null  object 
 15  emp.var.rate    41188 non-null  float64
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  y               41188 non-null  object 
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

3.4 Univariable Check

3.4.1 Numerical Columns

```python
# Numerical Columns
numerical_columns = ['age', 'duration', 'campaign', 'pdays', 'previous',
                     'emp.var.rate', 'cons.price.idx', 'cons.conf.idx',
                     'euribor3m', 'nr.employed']

plt.figure(figsize=(12, 8))
for i, column in enumerate(numerical_columns, 1):
    plt.subplot(3, 4, i)
    plt.hist(df[column], bins=20, color='skyblue', edgecolor='black', linewidth=1.5)
    plt.title(column)
    plt.xlabel('Value')
    plt.ylabel('Frequency')

plt.tight_layout()
plt.show()
```

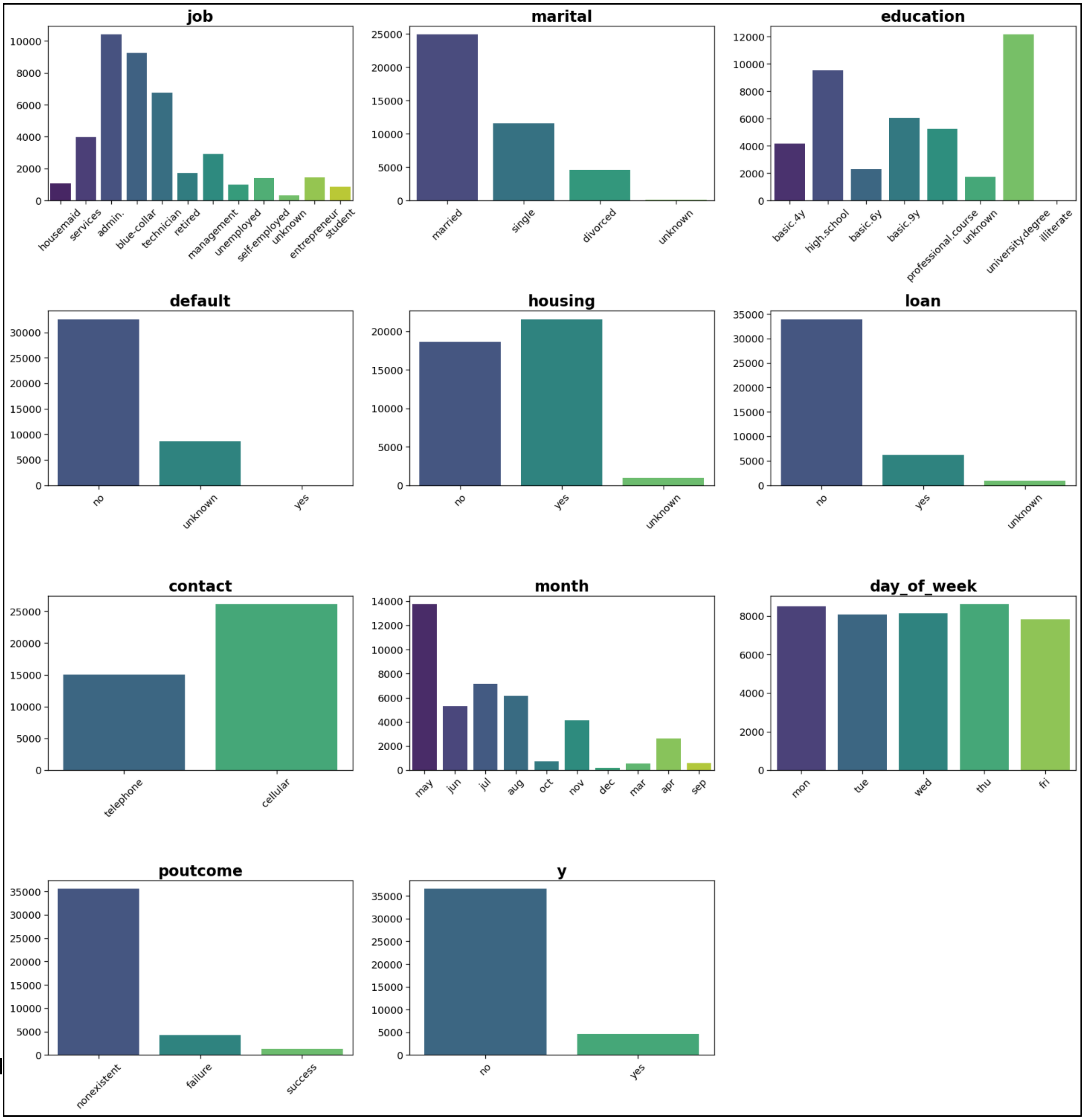
✓ 22.9s Python



Hozana Reis

3.4.2 Categorical Columns

```python
categorical_columns = ['job', 'marital', 'education', 'default', 'housing', 'loan',
                       'contact', 'month', 'day_of_week', 'poutcome', 'y']

plt.figure(figsize=(20, 30))
for i, column in enumerate(categorical_columns, 1):
    plt.subplot(6, 3, i)
    sns.countplot(data=df, x=column, palette='viridis')
    plt.title(column, fontsize=14, fontweight='bold')
    plt.xlabel(None)
    plt.ylabel(None)
    plt.xticks(rotation=45)

plt.tight_layout()
plt.show()
```



H

```python
summary_stats = df.describe()
summary_stats
```

Python

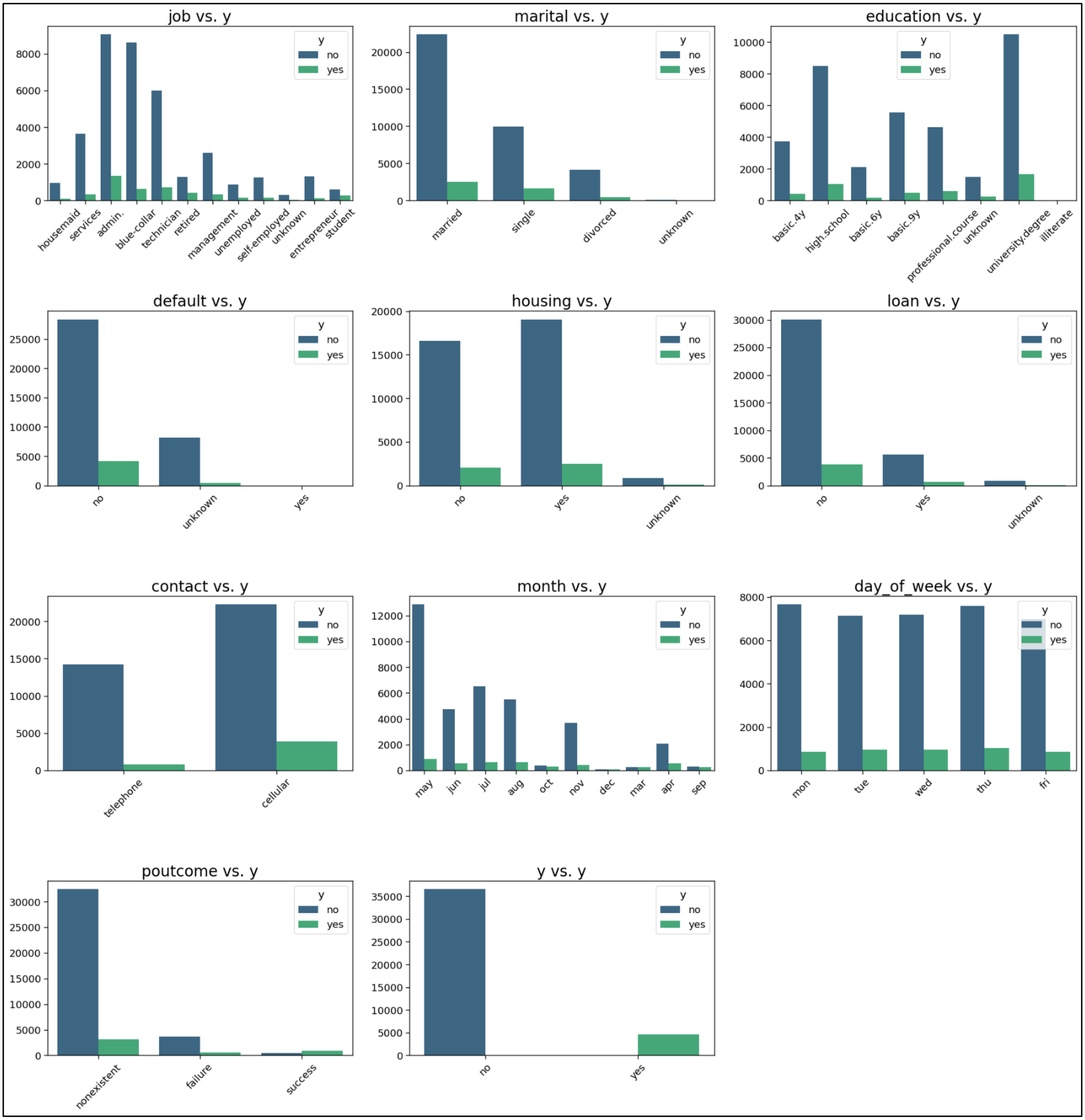
	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000
mean	40.02406	258.285010	2.567593	962.475454	0.172963	0.081886	93.575664	-40.502600	3.621291	5167.035911
std	10.42125	259.279249	2.770014	186.910907	0.494901	1.570960	0.578840	4.628198	1.734447	72.251528
min	17.00000	0.000000	1.000000	0.000000	0.000000	-3.400000	92.201000	-50.800000	0.634000	4963.600000
25%	32.00000	102.000000	1.000000	999.000000	0.000000	-1.800000	93.075000	-42.700000	1.344000	5099.100000
50%	38.00000	180.000000	2.000000	999.000000	0.000000	1.100000	93.749000	-41.800000	4.857000	5191.000000
75%	47.00000	319.000000	3.000000	999.000000	0.000000	1.400000	93.994000	-36.400000	4.961000	5228.100000
max	98.00000	4918.000000	56.000000	999.000000	7.000000	1.400000	94.767000	-26.900000	5.045000	5228.100000

3.5 Bivariable Check

3.5.1 Categorical Columns

```python
# Bivariable check

# Categorical
plt.figure(figsize=(20, 30))
for i, column in enumerate(categorical_columns, 1):
    plt.subplot(6, 3, i)
    sns.countplot(data=df, x=column, hue='y', palette='viridis')
    plt.title(f'{column} vs. y')
    plt.xlabel(None)
    plt.ylabel(None)
    plt.xticks(rotation=45)

plt.tight_layout()
plt.show()
```

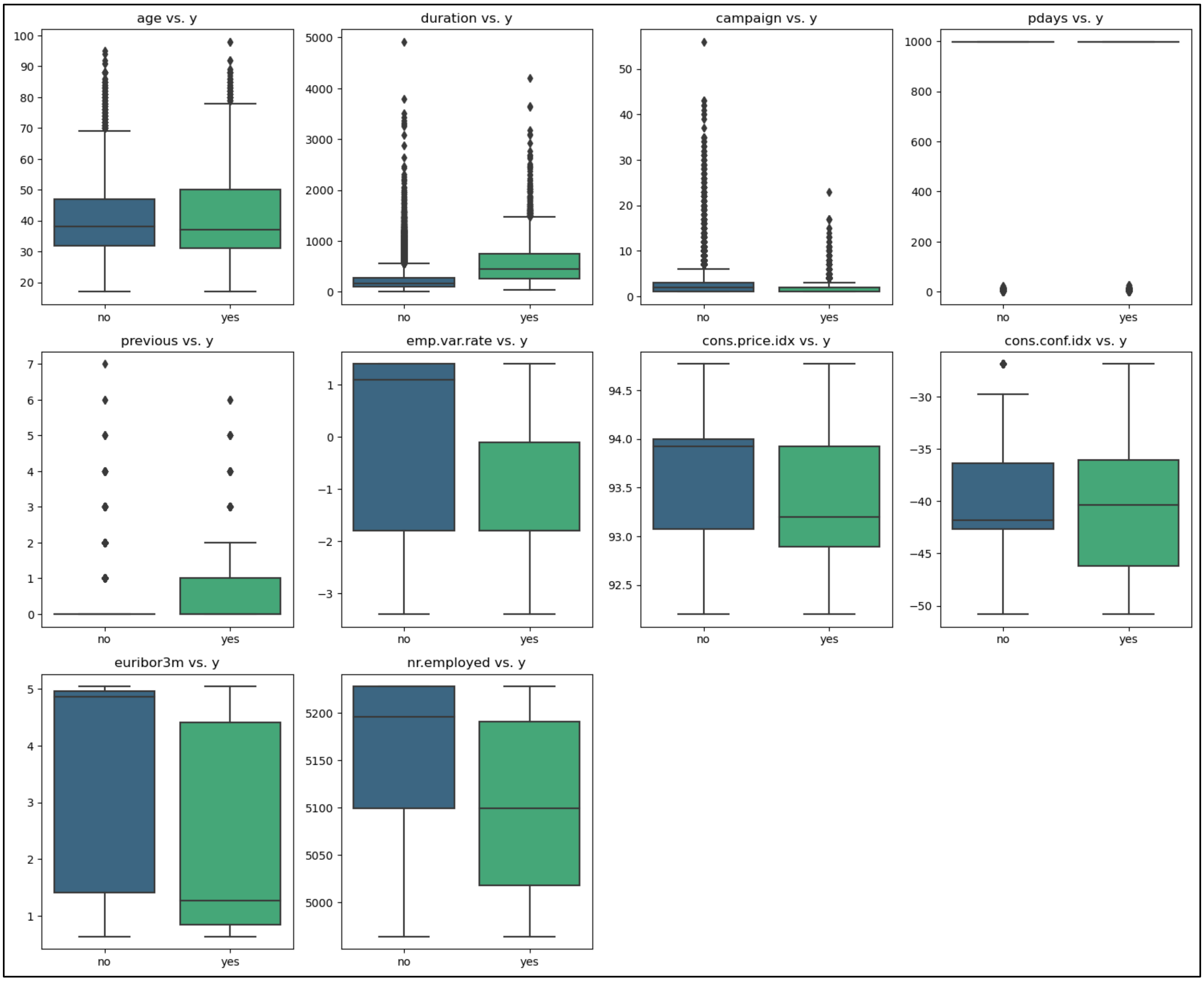
✓ 15.8s Python


job vs. y
marital vs. y
education vs. y
default vs. y
housing vs. y
loan vs. y
contact vs. y
month vs. y
day_of_week vs. y
poutcome vs. y
y vs. y
y
no
yes
housemaid
services
admin.
blue-collar
technician
retired
management
unemployed
self-employed
unknown
entrepreneur
student
married
single
divorced
basic.4y
high.school
basic.6y
basic.9y
professional.course
university.degree
illiterate
telephone
cellular
may
jun
jul
aug
oct
nov
dec
mar
apr
sep
mon
tue
wed
thu
fri
nonexistent
failure
success

Hozana Reis

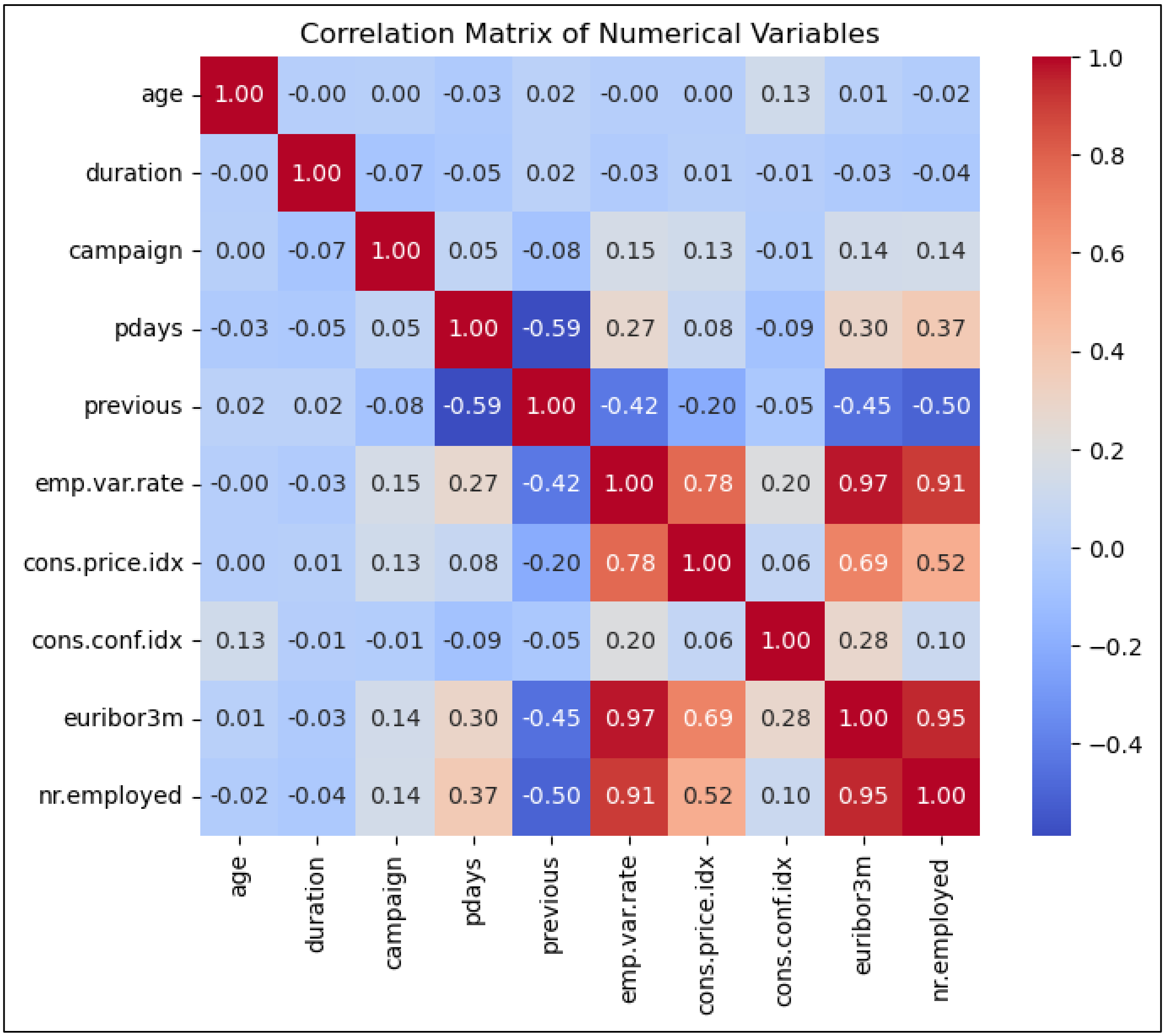
3.5.2 Numerical Columns

```python
# Numerical

plt.figure(figsize=(15, 20))
for i, column in enumerate(numerical_columns, 1):
    plt.subplot(5, 4, i)
    sns.boxplot(data=df, x='y', y=column, palette='viridis')
    plt.title(f'{column} vs. y')
    plt.xlabel(None)
    plt.ylabel(None)

plt.tight_layout()
plt.show()
```
Python



3.6 Correlation

```python
# correlation

# Compute the correlation matrix
correlation_matrix = df[numerical_columns].corr()


plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", square=True)
plt.title('Correlation Matrix of Numerical Variables')
plt.show()
```
Python



4. Data processing

I decided to remove the columns with high correlation (More than 0.95)

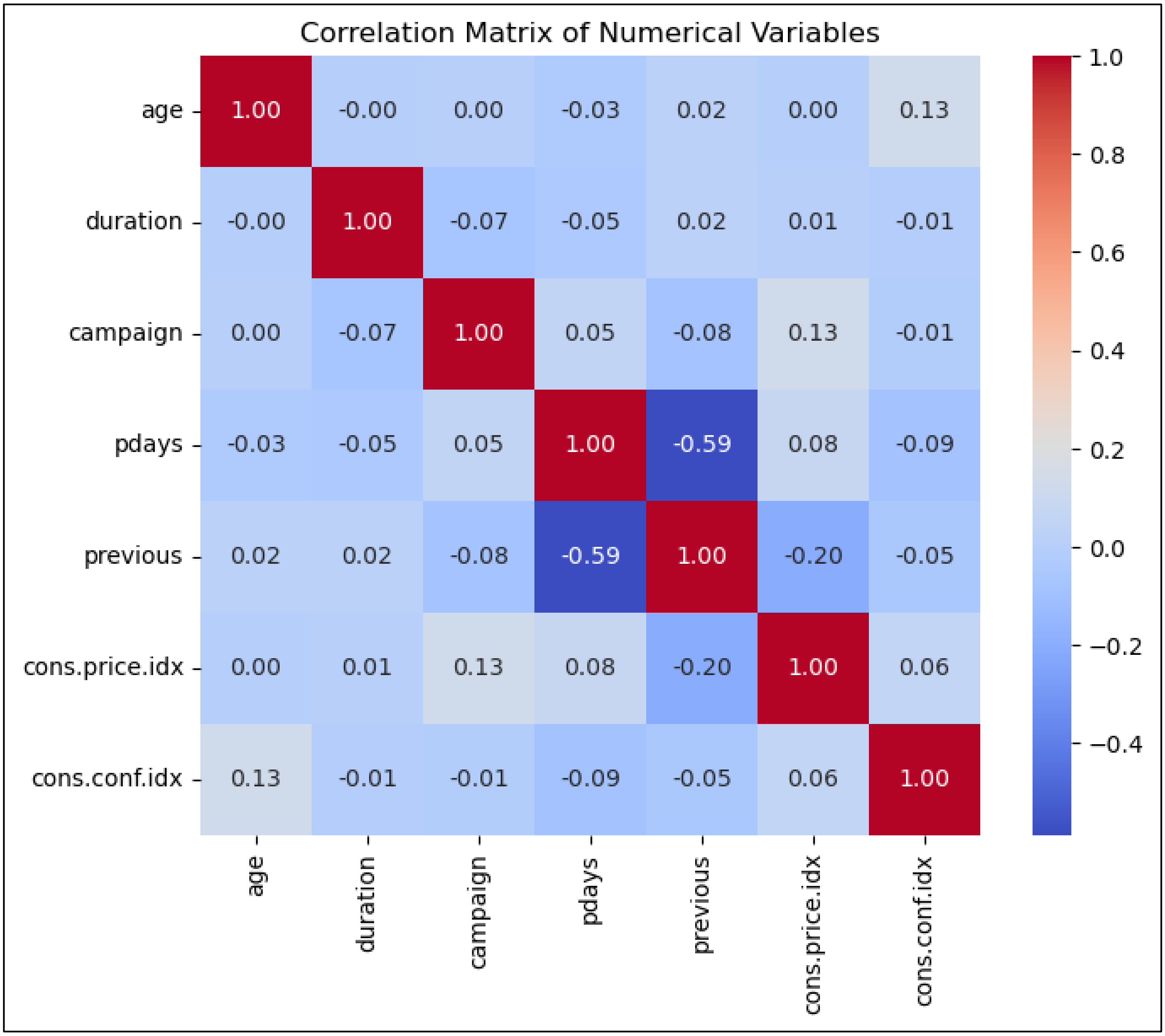
```
# Removing columns with high correlation ( More than 0.95)
variables_to_remove = ['euribor3m', 'nr.employed','emp.var.rate']
#drop
df_filtered = df.drop(variables_to_remove, axis=1)

print(df_filtered.head(5))
```

Python

```
   age        job  marital    education  default housing loan    contact  \
0   56  housemaid  married     basic.4y       no      no   no  telephone
1   57   services  married  high.school  unknown      no   no  telephone
2   37   services  married  high.school       no     yes   no  telephone
3   40     admin.  married     basic.6y       no      no   no  telephone
4   56   services  married  high.school       no      no  yes  telephone

  month day_of_week  duration  campaign  pdays  previous     poutcome  \
0   may         mon       261         1    999         0  nonexistent
1   may         mon       149         1    999         0  nonexistent
2   may         mon       226         1    999         0  nonexistent
3   may         mon       151         1    999         0  nonexistent
4   may         mon       307         1    999         0  nonexistent

   cons.price.idx  cons.conf.idx   y
0          93.994          -36.4  no
1          93.994          -36.4  no
2          93.994          -36.4  no
3          93.994          -36.4  no
4          93.994          -36.4  no
```

```
# checking the correlation again

# Numerical Columns
numerical_columns2 = ['age', 'duration', 'campaign', 'pdays', 'previous',
                      'cons.price.idx', 'cons.conf.idx'
                      ]

# Compute the correlation matrix
correlation_matrix = df_filtered[numerical_columns2].corr()
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", square=True)
plt.title('Correlation Matrix of Numerical Variables')
plt.show()
```

Python



I decided to keep the columns I think is relevant to the model.

```python
# Keeping the column I think is relevant to the model

variables_to_remove2 = ['contact', 'month','day_of_week','poutcome']
#drop
df_filtered = df_filtered.drop(variables_to_remove2, axis=1)
df_filtered.columns
```

✓ 0.0s Python

```
Index(['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
       'duration', 'campaign', 'pdays', 'previous', 'cons.price.idx',
       'cons.conf.idx', 'y'],
      dtype='object')
```

4.1 Categorical Treatment

-- Marital

```python
df_filtered['marital'].value_counts()
```

0.0s Python

```
marital
married     24928
single      11568
divorced     4612
unknown        80
Name: count, dtype: int64
```

Marital treatment decision: Remove category "Unknown"

```python
df_filtered = df_filtered[df_filtered['marital'] != 'unknown']
df_filtered['marital'].value_counts()
```

0.0s Python

```
marital
married     24928
single      11568
divorced     4612
Name: count, dtype: int64
```

-- Housing

```python
df_filtered['housing'].value_counts()
```

0.0s Python

```
housing
yes        21541
no         18578
unknown      989
Name: count, dtype: int64
```

Housing treatment decision: Remove category "Unknown"

```python
df_filtered = df_filtered[df_filtered['housing'] != 'unknown']
df_filtered['housing'].value_counts()
```

0.0s Python

```
housing
yes    21541
no     18578
Name: count, dtype: int64
```

-- Loan

Loan column doesn't need to remove the unkown category because as removing from the others it also removed from the Loan column

-- Education

Create a new category called " basic.education" by replacing the values 'basic.4y', 'basic.6y', and 'basic.9y'

```python
df_filtered['education'] = df_filtered['education'].replace(['basic.4y', 'basic.6y', 'basic.9y'],
                                                            'basic.education')
df_filtered['education'].value_counts()
```

✓ 0.0s Python

```
education
basic.education        12166
university.degree      11860
high.school             9281
professional.course     5112
unknown                 1682
illiterate                18
Name: count, dtype: int64
```

-- Age

Age grouping by Equal-wigth Binning : Divide the range of ages into a specified number of equal-width intervals. This approach ensures that each interval has the same width, but it may not capture variations in the distribution of ages.

```python
num_bins = 5
# Create equal-width bins for ages
df_filtered['age_group'] = pd.cut(df_filtered['age'], bins=num_bins, labels=[f'Group {i+1}'
                                  for i in range(num_bins)])

df_filtered['age_group'].value_counts()
```

✓ 0.0s Python

```
age_group
Group 2    19635
Group 1    12649
Group 3     7230
Group 4      508
Group 5       97
Name: count, dtype: int64
```

```python
# Print the boundaries of each age group
print("Age Group Boundaries:")
print(df_filtered.groupby('age_group')['age'].min())
print(df_filtered.groupby('age_group')['age'].max())
```

Python

```
Age Group Boundaries:
age_group
Group 1    17
Group 2    34
Group 3    50
Group 4    66
Group 5    82
Name: age, dtype: int64
age_group
Group 1    33
Group 2    49
Group 3    65
Group 4    81
Group 5    98
Name: age, dtype: int64
```

```python
# removing age from df
df_filtered = df_filtered.drop(columns=['age'])
print(df_filtered.head())
```

✓ 0.0s

Python

```
         job  marital        education  default housing loan  duration  \
0  housemaid  married  basic.education       no      no   no       261
1   services  married      high.school  unknown      no   no       149
2   services  married      high.school       no     yes   no       226
3     admin.  married  basic.education       no      no   no       151
4   services  married      high.school       no      no  yes       307

   campaign  pdays  previous  cons.price.idx  cons.conf.idx   y age_group
0         1    999         0          93.994          -36.4  no   Group 3
1         1    999         0          93.994          -36.4  no   Group 3
2         1    999         0          93.994          -36.4  no   Group 2
3         1    999         0          93.994          -36.4  no   Group 2
4         1    999         0          93.994          -36.4  no   Group 3
```

```python
cat_columns = ['job', 'marital', 'education', 'default', 'housing',
               'loan', 'age_group','y']

# Initialize LabelEncoder
label_encoder = LabelEncoder()

# Encode each categorical column
for column in cat_columns:
    df_filtered[column] = label_encoder.fit_transform(df_filtered[column])

df_filtered.head()
```

Python

	job	marital	education	default	housing	loan	duration	campaign	pdays	previous	cons.price.idx	cons.conf.id
0	3	1	0	0	0	0	261	1	999	0	93.994	-36.
1	7	1	1	1	0	0	149	1	999	0	93.994	-36.
2	7	1	1	0	1	0	226	1	999	0	93.994	-36.
3	0	1	0	0	0	0	151	1	999	0	93.994	-36.
4	7	1	1	0	0	1	307	1	999	0	93.994	-36.

4.2 Numerical Treatment

-- Feature Scaling

```python
num_columns = ['duration', 'campaign', 'pdays', 'previous', 'cons.price.idx', 'cons.conf.idx']

# Initialize StandardScaler
scaler = StandardScaler()

df_filtered[num_columns] = scaler.fit_transform(df_filtered[num_columns])
df_filtered.head()
```

Python

	job	marital	education	default	housing	loan	duration	campaign	pdays	previous	cons.price.idx	cons.cor
0	3	1	0	0	0	0	0.010084	-0.566986	0.195436	-0.349162	0.725917	0.88
1	7	1	1	1	0	0	-0.421805	-0.566986	0.195436	-0.349162	0.725917	0.88
2	7	1	1	0	1	0	-0.124881	-0.566986	0.195436	-0.349162	0.725917	0.88
3	0	1	0	0	0	0	-0.414093	-0.566986	0.195436	-0.349162	0.725917	0.88
4	7	1	1	0	0	1	0.187468	-0.566986	0.195436	-0.349162	0.725917	0.88

5. Machine Learning Model

5.1 Splitting the Data into Train and Test

-- Split the data

```python
X = df_filtered.drop(columns=['y'])  # Features
y = df_filtered['y']  # Target variable

# Split the data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Print the shapes of the training and testing sets
print("Training set shape:", X_train.shape, y_train.shape)
print("Testing set shape:", X_test.shape, y_test.shape)
```

Python

```
Training set shape: (32095, 13) (32095,)
Testing set shape: (8024, 13) (8024,)
```

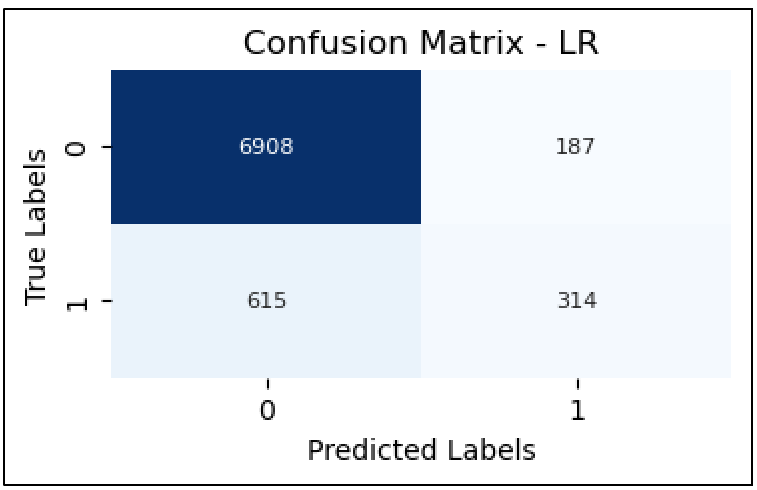
5.2 Classifiers

5.2.1 Logistic Regression

```python
from sklearn.linear_model import LogisticRegression # Library

model = LogisticRegression(random_state=42)

model.fit(X_train, y_train) # Train the model on the training set

y_pred_lr = model.predict(X_test) # Make predictions on the testing set

# Evaluate the model's accuracy
accuracy = accuracy_score(y_test, y_pred_lr)
print("Accuracy:", accuracy)

# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_lr)
plt.figure(figsize=(4, 2))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=False, annot_kws={"fontsize":8})
plt.title('Confusion Matrix - LR')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```

Python

```
Accuracy: 0.900049850448654
```



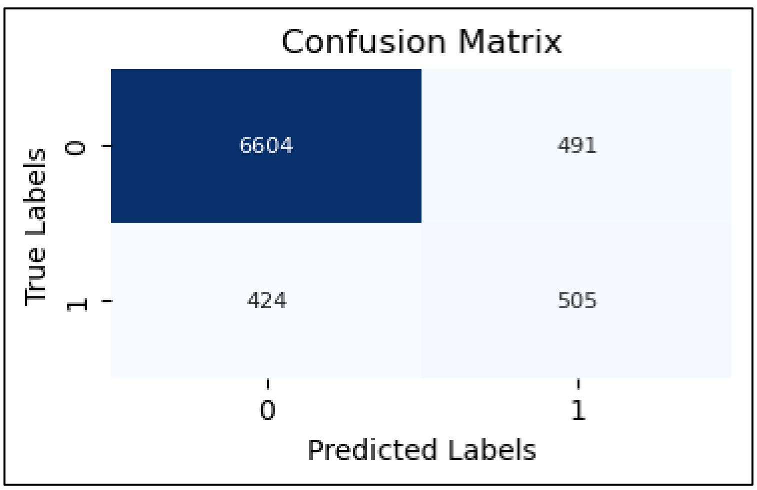
Logistic Regression achieved an accuracy of 90.0% and demonstrated good performance in classifying the target variable. It correctly classified 6908 instances of the negative class (no) and 314 instances of the positive class (yes).

5.2.2 Decision Tree

```python
from sklearn.tree import DecisionTreeClassifier

dt_classifier = DecisionTreeClassifier()

dt_classifier.fit(X_train, y_train) # Train the decision tree classifier

y_pred_dt = dt_classifier.predict(X_test) # Make predictions on the testing set


accuracy_dt = accuracy_score(y_test, y_pred_dt)
print("Accuracy:", accuracy_dt)

# Calculate confusion matrix
conf_matrix_dt = confusion_matrix(y_test, y_pred_dt)
plt.figure(figsize=(4, 2))
sns.heatmap(conf_matrix_dt, annot=True, fmt='d', cmap='Blues', cbar=False, annot_kws={"fontsize":8})
plt.title('Confusion Matrix - DT')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```

Python

```
Accuracy: 0.8859670987038883
```



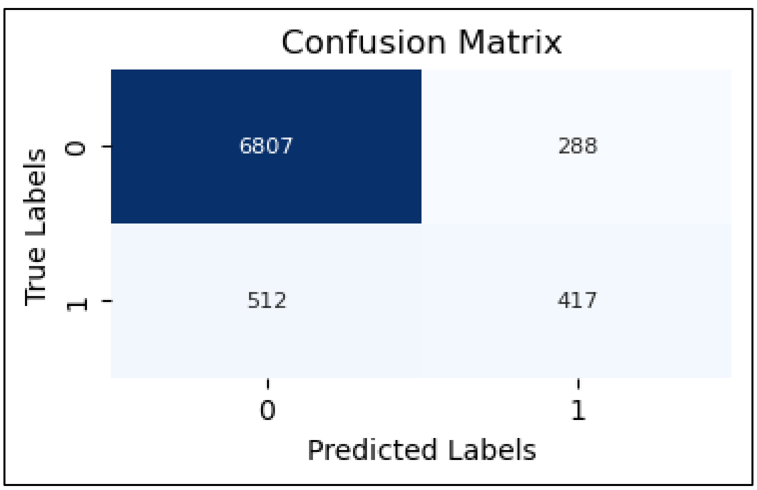
Decision Tree achieved an accuracy of 88.3%. It correctly classified 6604 instances of the negative class and 505 instances of the positive class.

5.2.3 Random Forest

```python
from sklearn.ensemble import RandomForestClassifier # Library

rf_classifier = RandomForestClassifier()
rf_classifier.fit(X_train, y_train) # Train classifier


y_pred_rf = rf_classifier.predict(X_test) # Predict on the test set

# Calculate accuracy
accuracy_rf = accuracy_score(y_test, y_pred_rf)
print("Accuracy:", accuracy_rf)

# Calculate confusion matrix
conf_matrix_rf = confusion_matrix(y_test, y_pred_rf)
plt.figure(figsize=(4, 2))
sns.heatmap(conf_matrix_rf, annot=True, fmt='d', cmap='Blues', cbar=False, annot_kws={"fontsize":8})
plt.title('Confusion Matrix - RF')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```

Python

```
Accuracy: 0.9002991026919243
```



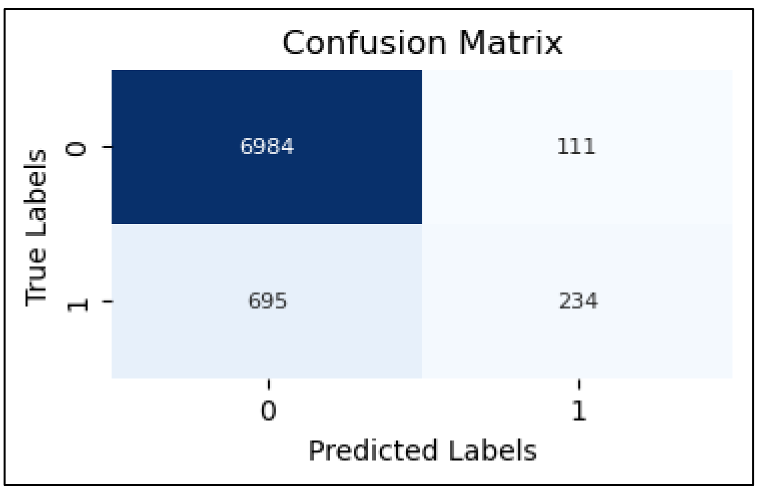
Random Forest achieved an accuracy of 90.2% and demonstrated robust performance. It correctly classified 6807 instances of the negative class and 417 instances of the positive class.

5.2.4 Support Vector Machines (SVM)

```
from sklearn.svm import SVC # Library


svm_classifier = SVC()
svm_classifier.fit(X_train, y_train) # Train classifier


y_pred_svm = svm_classifier.predict(X_test) # Predict on the test set

# Calculate accuracy
accuracy_svm = accuracy_score(y_test, y_pred_svm)
print("Accuracy:", accuracy_svm)

# Calculate confusion matrix
conf_matrix_svm = confusion_matrix(y_test, y_pred_svm)
plt.figure(figsize=(4, 2))
sns.heatmap(conf_matrix_svm, annot=True, fmt='d', cmap='Blues', cbar=False, annot_kws={"fontsize":8})
plt.title('Confusion Matrix - SVM')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```

Python

```
Accuracy: 0.8995513459621136
```



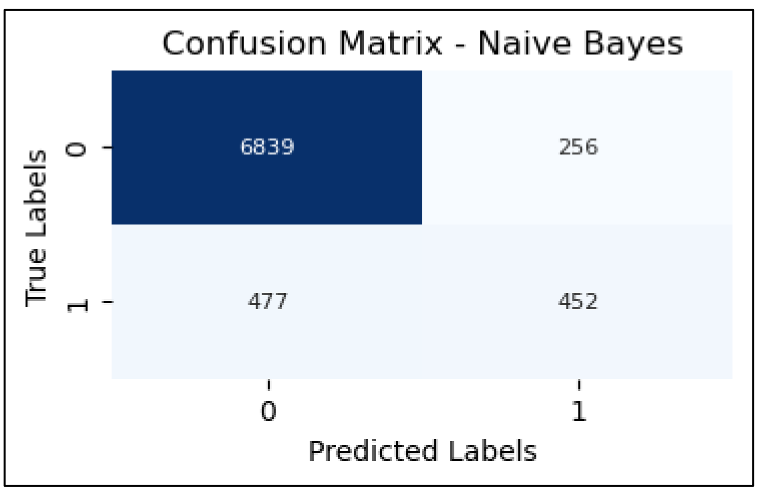
SVM achieved an accuracy of 90.0%. It correctly classified 6984 instances of the negative class and 234 instances of the positive class.

5.2.5 Gradient Boosting

```python
from sklearn.ensemble import GradientBoostingClassifier # Library


gb_classifier = GradientBoostingClassifier()
gb_classifier.fit(X_train, y_train) # Train classifier

y_pred_gb = gb_classifier.predict(X_test) # Predict on the test set


# Calculate accuracy
accuracy_gb = accuracy_score(y_test, y_pred_gb)
print("Accuracy:", accuracy_gb)

# Calculate confusion matrix
conf_matrix_gb = confusion_matrix(y_test, y_pred_gb)
plt.figure(figsize=(4, 2))
sns.heatmap(conf_matrix_gb, annot=True, fmt='d', cmap='Blues', cbar=False, annot_kws={"fontsize":8})
plt.title('Confusion Matrix - NB')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```

Python

```
Accuracy: 0.9086490528414756
```



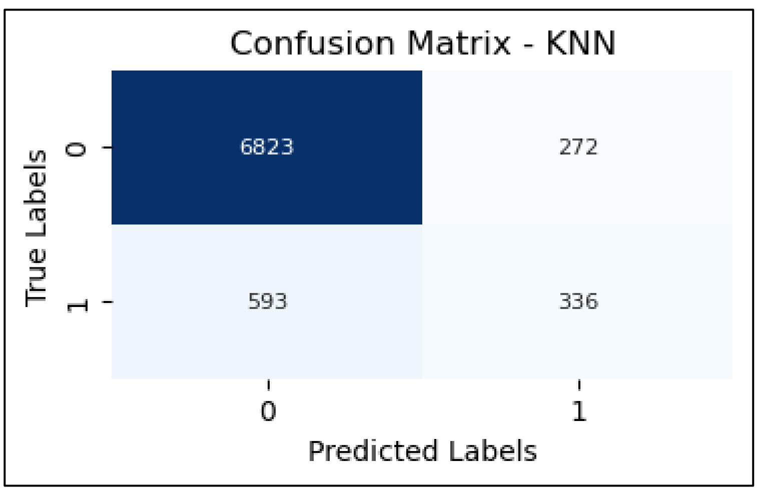
Gradient Boosting achieved an accuracy of 90.9% and demonstrated excellent performance. It correctly classified 6839 instances of the negative class and 452 instances of the positive class.

5.2.6 K- Nearest Neighbors (KNN)

```python
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=5)

knn.fit(X_train, y_train) # Train the KNN classifier

y_pred_knn = knn.predict(X_test) # Predict on the testing set

accuracy_knn = accuracy_score(y_test, y_pred_knn)
print("KNN Accuracy:", accuracy_knn)


cm_knn = confusion_matrix(y_test, y_pred_knn)

# Confusion matrix
plt.figure(figsize=(4, 2))
sns.heatmap(cm_knn, annot=True, fmt='d', cmap='Blues', cbar=False, annot_kws={"fontsize":8})
plt.title('Confusion Matrix - KNN')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```

Python

```
KNN Accuracy: 0.892198404785643
```



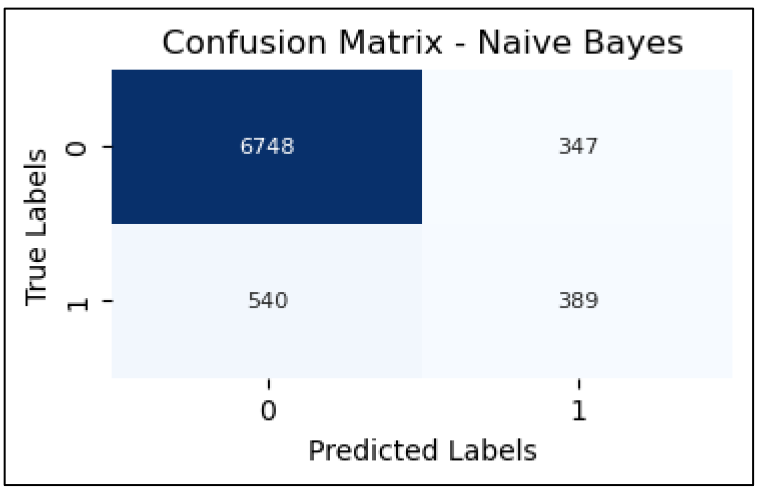
KNN achieved an accuracy of 89.2%. It correctly classified 6823 instances of the negative class and 336 instances of the positive class.

5.2.7 Naïve Bayes

```python
from sklearn.naive_bayes import GaussianNB

nb = GaussianNB()


nb.fit(X_train, y_train) # Train the Naive Bayes classifier
y_pred_nb = nb.predict(X_test) # Predict on the testing set

accuracy_nb = accuracy_score(y_test, y_pred_nb)
print("Naive Bayes Accuracy:", accuracy_nb)

cm_nb = confusion_matrix(y_test, y_pred_nb)

# Confusion matrix for Naive Bayes
plt.figure(figsize=(4, 2))
sns.heatmap(cm_nb, annot=True, fmt='d', cmap='Blues', cbar=False, annot_kws={"fontsize":8})
plt.title('Confusion Matrix - Naive Bayes')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```

Python

```
Naive Bayes Accuracy: 0.889456630109671
```



Naive Bayes achieved an accuracy of 88.9%. It correctly classified 6748 instances of the negative class and 389 instances of the positive class.

5.3 1st Model Evaluation

Summarizing this part: Gradient Boosting achieved the highest accuracy among the classifiers tested, followed closely by Random Forest. These models demonstrated robust performance in predicting the target variable, Let's check it further.

Double-check if the Gradient Boosting and Random Forest are the best among other classifiers comparing through Precision, Recall, and F1 score.

```python
# Define the evaluation function
def evaluate_model(y_true, y_pred):
    accuracy = accuracy_score(y_true, y_pred)
    precision = precision_score(y_true, y_pred, pos_label=1)
    recall = recall_score(y_true, y_pred, pos_label=1)
    f1 = f1_score(y_true, y_pred, pos_label=1)
    return accuracy, precision, recall, f1

# Evaluate each classifier
classifiers = {
    "Logistic Regression": y_pred_lr,
    "Decision Tree": y_pred_dt,
    "Gradient Boosting": y_pred_gb,
    "Random Forest": y_pred_rf,
    "Support Vector Machine (SVM)": y_pred_svm,
    "K-Nearest Neighbors (KNN)": y_pred_knn,
    "Naive Bayes": y_pred_nb
}

for clf_name, y_pred in classifiers.items():
    accuracy, precision, recall, f1 = evaluate_model(y_test, y_pred)
    print(f"{clf_name}:")
    print(f"  Accuracy: {accuracy:.4f}")
    print(f"  Precision: {precision:.4f}")
    print(f"  Recall: {recall:.4f}")
    print(f"  F1 Score: {f1:.4f}")
```

Python

```
Random Forest:
  Accuracy: 0.9003
  Precision: 0.5915
  Recall: 0.4489
  F1 Score: 0.5104
Support Vector Machine (SVM):
  Accuracy: 0.8996
  Precision: 0.6783
  Recall: 0.2519
  F1 Score: 0.3673
```

```
K-Nearest Neighbors (KNN):
  Accuracy: 0.8922
  Precision: 0.5526
  Recall: 0.3617
  F1 Score: 0.4372
Naive Bayes:
  Accuracy: 0.8895
  Precision: 0.5285
  Recall: 0.4187
  F1 Score: 0.4673
```

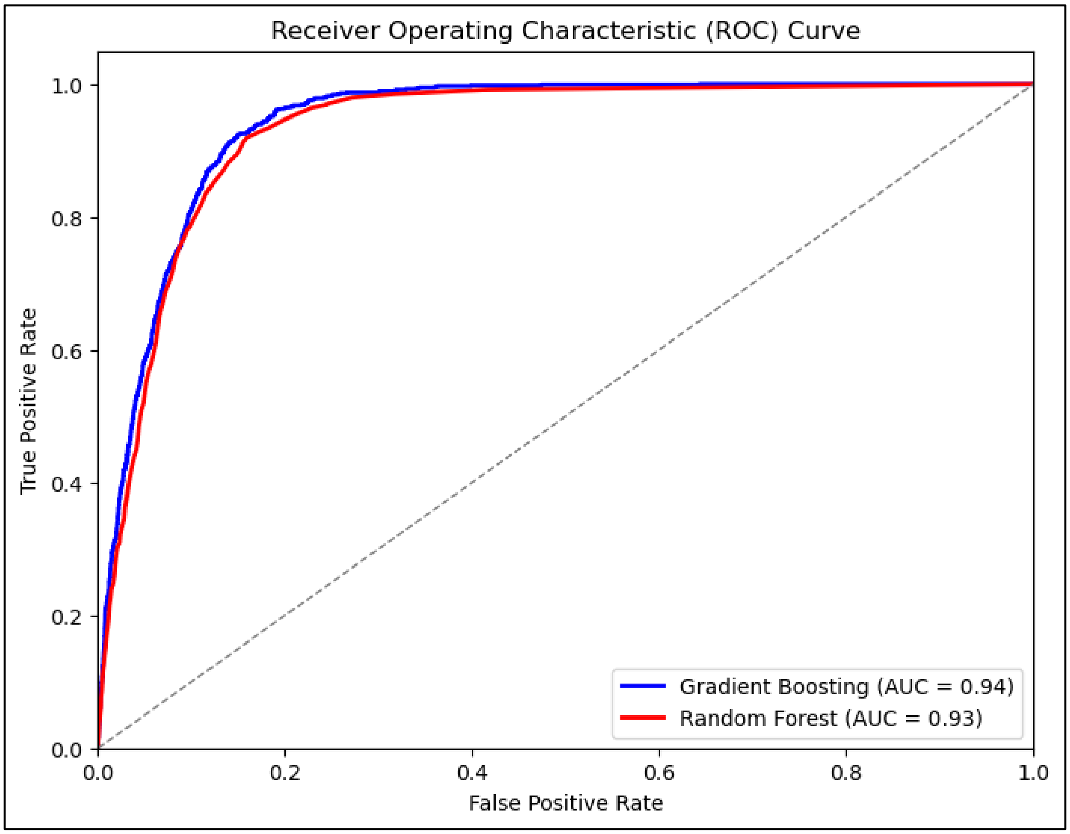
```
Logistic Regression:
  Accuracy: 0.9000
  Precision: 0.6267
  Recall: 0.3380
  F1 Score: 0.4392
Decision Tree:
  Accuracy: 0.8860
  Precision: 0.5070
  Recall: 0.5436
  F1 Score: 0.5247
Gradient Boosting:
  Accuracy: 0.9086
  Precision: 0.6384
  Recall: 0.4865
  F1 Score: 0.5522
```

5.4 ROC Curve from Gradient Boosting and Random Forest

ROC Curve form Gradient Boosting and Random Forest

```python
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

# Compute predicted probabilities for Gradient Boosting and Random Forest
y_prob_gb = gb_classifier.predict_proba(X_test)[:, 1]
y_prob_rf = rf_classifier.predict_proba(X_test)[:, 1]

# Compute ROC curve and ROC area for Gradient Boosting
fpr_gb, tpr_gb, _ = roc_curve(y_test, y_prob_gb)
roc_auc_gb = auc(fpr_gb, tpr_gb)

# Compute ROC curve and ROC area for Random Forest
fpr_rf, tpr_rf, _ = roc_curve(y_test, y_prob_rf)
roc_auc_rf = auc(fpr_rf, tpr_rf)

# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr_gb, tpr_gb, color='blue', lw=2, label=f'Gradient Boosting (AUC = {roc_auc_gb:.2f})')
plt.plot(fpr_rf, tpr_rf, color='red', lw=2, label=f'Random Forest (AUC = {roc_auc_rf:.2f})')
plt.plot([0, 1], [0, 1], color='gray', lw=1, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

Python



5.5 Feature Importance

Feature importance analysis is a technique used to determine the relative importance of each feature in predicting the target variable.

Extracting feature importance from Gradient Boosting and Random Forest classifiers, considering they exhibited the best performance

5.5.1 Gradient Boosting Feature Importance

```python
feature_importances_gb = gb_classifier.feature_importances_

# Display feature importances
feature_importance_df_gb = pd.DataFrame
({'Feature': X_train.columns, 'Importance': feature_importances_gb})
feature_importance_df_gb = feature_importance_df_gb.sort_values(by='Importance', ascending=False)
print("Gradient Boosting Feature Importance:")
print(feature_importance_df_gb)
```

Python

```
Gradient Boosting Feature Importance:
          Feature  Importance
6        duration    0.449408
8           pdays    0.211973
11  cons.conf.idx    0.192609
10 cons.price.idx    0.114420
12      age_group    0.009168
9        previous    0.008324
3         default    0.005169
2       education    0.003643
7        campaign    0.003206
0             job    0.001631
1         marital    0.000203
5            loan    0.000139
4         housing    0.000106
```

5.5.2 Random Forest Feature Importance

```python
feature_importances_rf = rf_classifier.feature_importances_

# Display feature importances
feature_importance_df_rf = pd.DataFrame
({'Feature': X_train.columns, 'Importance': feature_importances_rf})
feature_importance_df_rf = feature_importance_df_rf.sort_values(by='Importance', ascending=False)
print("Random Forest Feature Importance:")
print(feature_importance_df_rf)
```

✓ 0.8s Python

```
Random Forest Feature Importance:
          Feature  Importance
6        duration    0.383752
11  cons.conf.idx    0.107900
10 cons.price.idx    0.085974
8           pdays    0.080620
0             job    0.068586
7        campaign    0.060461
2       education    0.049182
12      age_group    0.045446
9        previous    0.033405
1         marital    0.031473
4         housing    0.025164
5            loan    0.017168
3         default    0.010871
```

5.5.3 Feature Importance Conclusion (Gradient Boosting)

Duration: This feature has the highest importance, indicating that the duration of the call has a significant impact on the outcome.

Pdays: The number of days that passed after the client was last contacted from a previous campaign is also a crucial factor.

Cons.conf.idx and Cons.price.idx: These are economic indicators, suggesting that the overall economic context plays a role.

Age Group and Previous Contacts: These features have relatively lower importance but still contribute to the model.

5.5.4 Feature Importance Conclusion (Random Forest)

Duration: Similarly, the duration of the call is the most critical predictor in the Random Forest model.

Cons.conf.idx and Cons.price.idx: Economic indicators remain significant in this model as well.

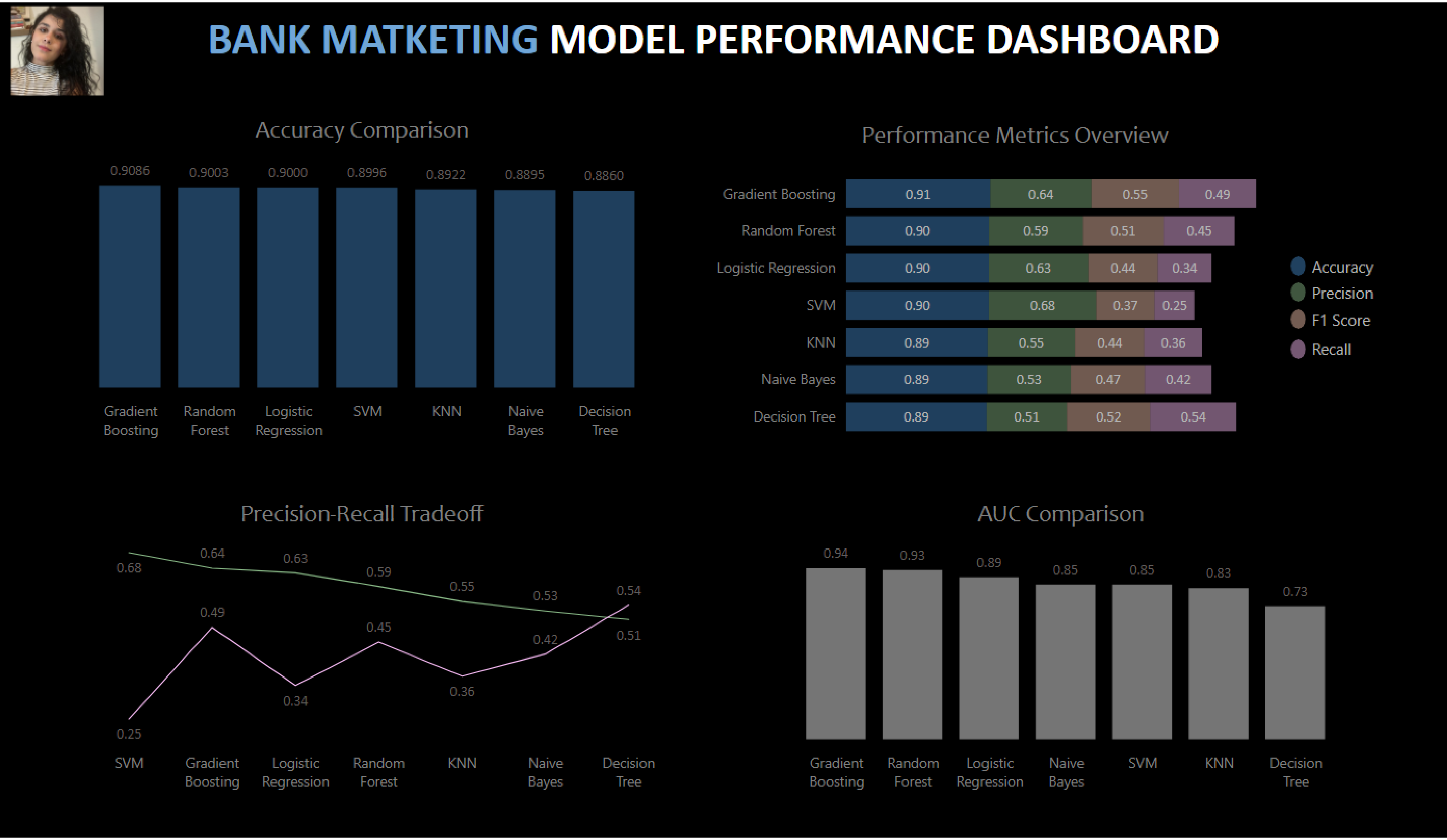
Job and Campaign: Job type and number of contacts during this campaign also have notable importance.

Education and Age Group: These features also contribute significantly to the model's predictions.

5.5.5 Feature Importance Conclusion

Both models highlight the importance of the call duration and economic indicators (cons.conf.idx and cons.price.idx). Other factors such as job type, education level, and age group also play essential roles in predicting the outcome of the marketing campaign. Overall, these insights can guide marketing strategies to focus on specific customer demographics and tailor communication strategies based on economic conditions and call duration.

6. Model Performance Dashboard



7. Conclusion

After integrating all classifiers into the Power BI dashboard and comparing their performance, it's evident that Gradient Boosting and Random Forest consistently outperform other classifiers. This conclusion is drawn from various performance metrics such as Accuracy, Precision, Recall, F1 Score, and AUC. Moreover, analyzing the feature importance reveals that the duration of the call holds significant importance for both classifiers. This insight suggests that investing time in client calls could be an effective strategy for the bank.