Loading Libraries

```
# Importing Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import mean_absolute_error, mean_squared_error
import os
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics
from sklearn.metrics import accuracy_score,precision_score, recall_score
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import GridSearchCV

pd.set_option('display.max_columns', None)
```

Loading Data

```
# Mounting the notebook to the drive to load the data
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
# Path for the data
path = "drive/MyDrive/Colab Notebooks/Data Mining/Project/Implementation/data/"
```

```
# Loading data
bank_add = pd.read_csv(path+'bank-additional/bank-additional-full.csv', delimiter = ';')
```

Data Exploration & Pre-Processing

```
# This function will give us the summary of data

# def data_summary(df):
#   row = {}
#   output = pd.DataFrame()
#   for i in df.columns:
#     row['ColumnName'] = i
#     row['Description'] = ''
#     row['ColumnType'] = df[i].dtype
#     row['#OfUniqueValues'] = df[i].nunique()
#     row['SampleData'] = df[i].unique()[:25]

#     output = output.append(row, ignore_index=True)
#   return output

# output = data_summary(bank_add)
# output.to_csv(path+'bank_add.csv', index = False)
```

```
bank_add
```

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaign	pdays	previous	poutcome	emp.var
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon	261	1	999	0	nonexistent	
1	57	services	married	high.school	unknown	no	no	telephone	may	mon	149	1	999	0	nonexistent	
2	37	services	married	high.school	no	yes	no	telephone	may	mon	226	1	999	0	nonexistent	
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon	151	1	999	0	nonexistent	
4	56	services	married	high.school	no	no	yes	telephone	may	mon	307	1	999	0	nonexistent	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
41183	73	retired	married	professional.course	no	yes	no	cellular	nov	fri	334	1	999	0	nonexistent	
41184	46	blue-collar	married	professional.course	no	no	no	cellular	nov	fri	383	1	999	0	nonexistent	
41185	56	retired	married	university.degree	no	yes	no	cellular	nov	fri	189	2	999	0	nonexistent	
41186	44	technician	married	professional.course	no	no	no	cellular	nov	fri	442	1	999	0	nonexistent	
41187	74	retired	married	professional.course	no	yes	no	cellular	nov	fri	239	3	999	1	failure	

41188 rows × 21 columns

```
bank_add.shape
```

```
(41188, 21)
```

```
bank_add.info()
```

```
<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
```

```
bank_add.dtypes
```

```
age                 int64
job                object
marital            object
education          object
default            object
housing            object
loan               object
contact            object
month              object
day_of_week        object
duration            int64
campaign            int64
pdays               int64
previous            int64
poutcome           object
emp.var.rate      float64
cons.price.idx    float64
cons.conf.idx     float64
euribor3m         float64
nr.employed       float64
y                  object
dtype: object
```

```
# replacing unknown values with NULL
bank_add = bank_add.replace('unknown',np.nan)
bank_add['pdays'] = bank_add['pdays'].replace(999,np.nan)
```

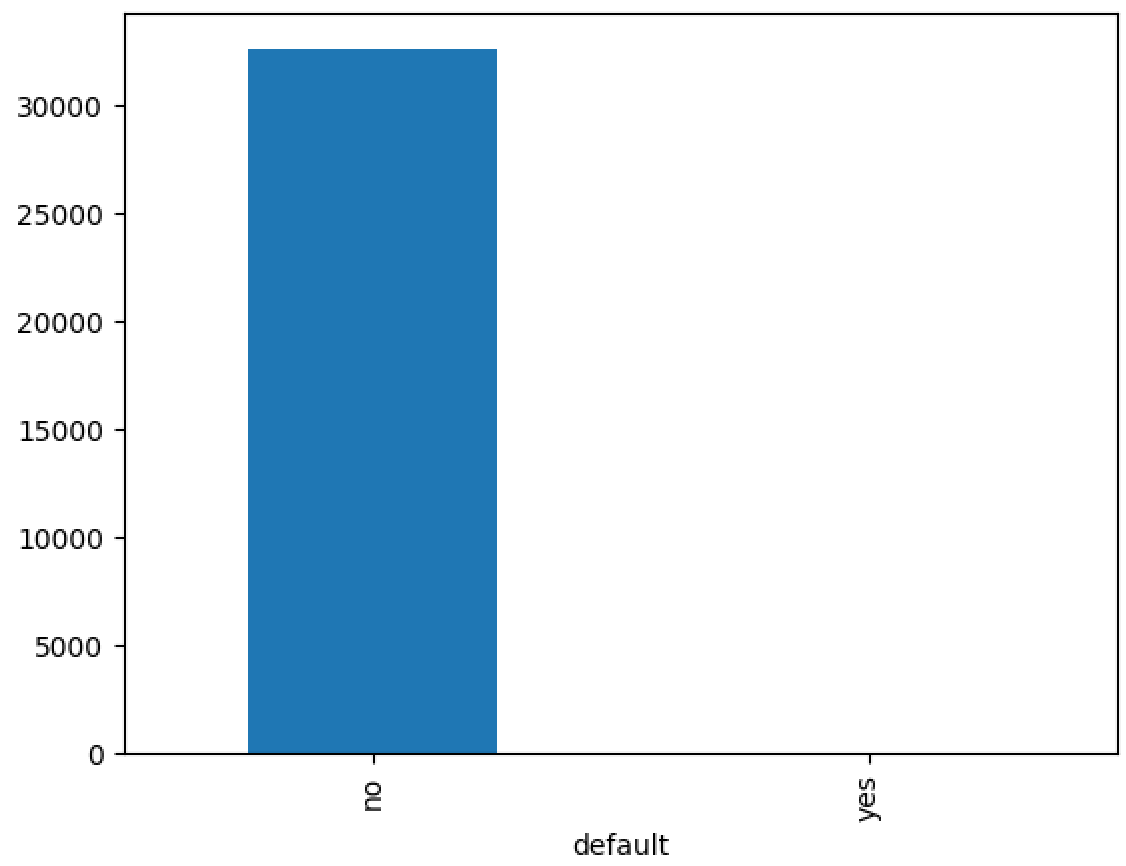
```
(bank_add.isnull().sum()/len(bank_add))*100 #count of null values
```

```
age                0.000000
job                0.801204
marital            0.194231
education          4.202680
default           20.872584
housing            2.403613
loan               2.403613
contact            0.000000
month              0.000000
day_of_week        0.000000
duration           0.000000
campaign           0.000000
previous           0.000000
poutcome           0.000000
emp.var.rate       0.000000
cons.price.idx     0.000000
cons.conf.idx      0.000000
euribor3m          0.000000
nr.employed        0.000000
y                  0.000000
dtype: float64
```

```
bank_add = bank_add.dropna(axis = 1, thresh = len(bank_add)*0.75) #Dropping columns with 75% of the records with null values
```

```
bank_add.groupby('default')['y'].count().plot(kind = 'bar')
```

```
<Axes: xlabel='default'>
```




```
bank_add = bank_add.drop('default', axis = 1) #dropping default column as it has only one value for all columns - 'no'
```

```
bank_add = bank_add.dropna() #dropping null in all columns
```

```
(bank_add.isnull().sum()/len(bank_add))*100 #count of null values
```

```
age          0.0
job          0.0
marital      0.0
education    0.0
housing      0.0
loan         0.0
```

```
contact           0.0
month             0.0
day_of_week       0.0
duration          0.0
campaign          0.0
previous          0.0
poutcome          0.0
emp.var.rate      0.0
cons.price.idx    0.0
cons.conf.idx     0.0
euribor3m         0.0
nr.employed       0.0
y                 0.0
dtype: float64
```

```
bank_add.shape
```

```
(38245, 19)
```

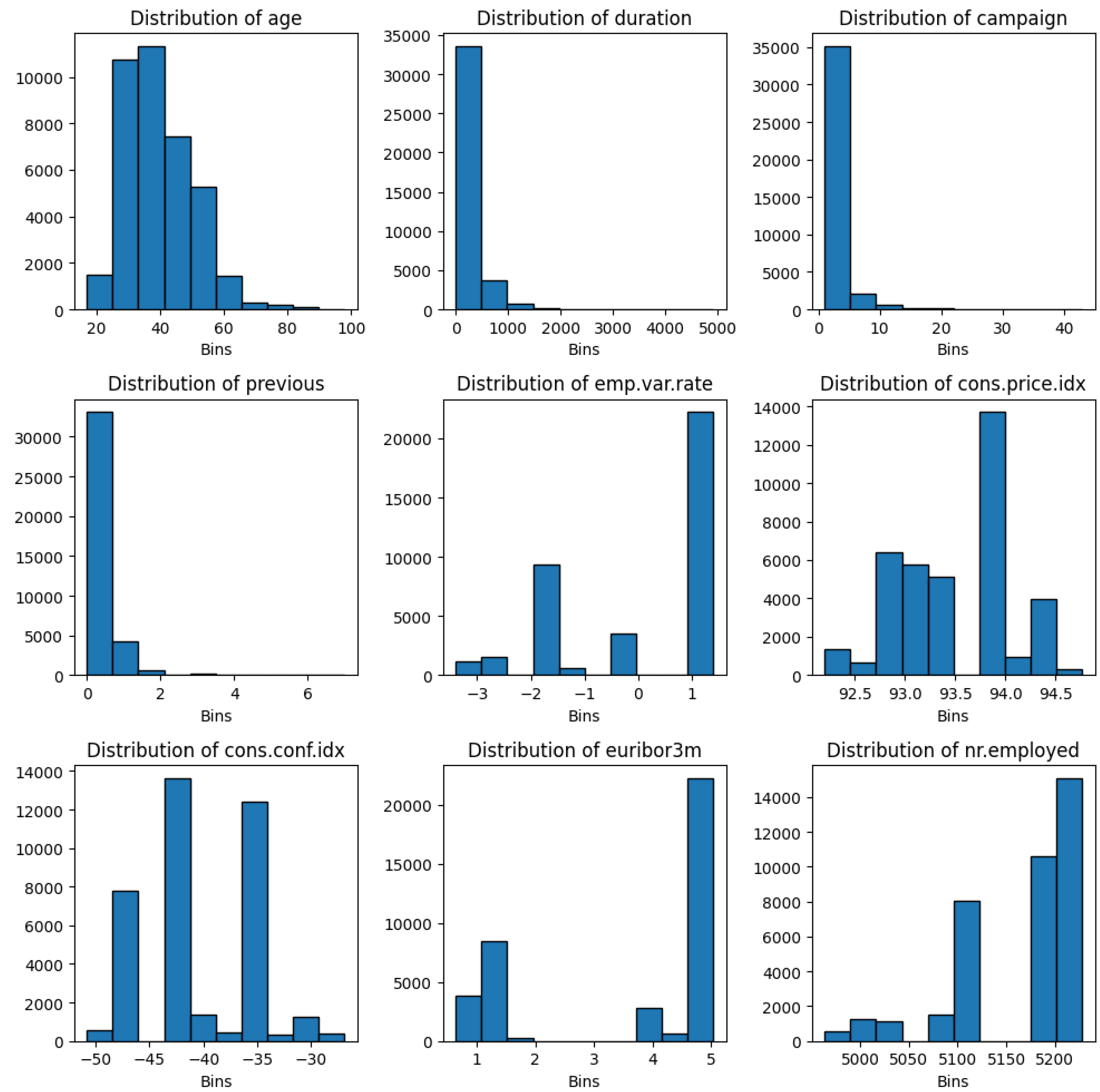
```
bank_add['job'] = bank_add['job'].replace('.',' ')
```

```
bank_add.describe()
```

	age	duration	campaign	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
count	38245.000000	38245.000000	38245.000000	38245.000000	38245.000000	38245.000000	38245.000000	38245.000000	38245.000000
mean	39.860871	258.207583	2.566662	0.170009	0.082861	93.570313	-40.541164	3.623298	5167.432566
std	10.289488	259.792638	2.767473	0.487169	1.565945	0.576367	4.623200	1.730226	71.760333
min	17.000000	0.000000	1.000000	0.000000	-3.400000	92.201000	-50.800000	0.634000	4963.600000
25%	32.000000	102.000000	1.000000	0.000000	-1.800000	93.075000	-42.700000	1.344000	5099.100000
50%	38.000000	180.000000	2.000000	0.000000	1.100000	93.444000	-41.800000	4.857000	5191.000000
75%	47.000000	319.000000	3.000000	0.000000	1.400000	93.994000	-36.400000	4.961000	5228.100000
max	98.000000	4918.000000	43.000000	7.000000	1.400000	94.767000	-26.900000	5.045000	5228.100000

```
numeric_variables = bank_add.columns[bank_add.dtypes != 'object'].tolist() #numerical columns
categorical_variables = bank_add.columns[bank_add.dtypes == 'object'].tolist() #cartegorical columns
categorical_variables.remove('y')
```

```
fig, ax = plt.subplots(3,3, figsize=(10,10))
index = 0
for i in range(3):
  for j in range(3):
    ax[i,j].hist(bank_add[numeric_variables[index]], edgecolor='black')
    ax[i,j].set_title("Distribution of "+str(numeric_variables[index]))
    ax[i,j].set_xlabel('Bins')
    index = index + 1
plt.tight_layout()
plt.show()
```




```
bank_add
```

	age	job	marital	education	housing	loan	contact	month	day_of_week	duration	campaign	previous	poutcome	emp.var.rate	cons.pric
0	56	housemaid	married	basic.4y	no	no	telephone	may	mon	261	1	0	nonexistent	1.1	
1	57	services	married	high.school	no	no	telephone	may	mon	149	1	0	nonexistent	1.1	
2	37	services	married	high.school	yes	no	telephone	may	mon	226	1	0	nonexistent	1.1	
3	40	admin.	married	basic.6y	no	no	telephone	may	mon	151	1	0	nonexistent	1.1	
4	56	services	married	high.school	no	yes	telephone	may	mon	307	1	0	nonexistent	1.1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
41183	73	retired	married	professional.course	yes	no	cellular	nov	fri	334	1	0	nonexistent	-1.1	
41184	46	blue-collar	married	professional.course	no	no	cellular	nov	fri	383	1	0	nonexistent	-1.1	
41185	56	retired	married	university.degree	yes	no	cellular	nov	fri	189	2	0	nonexistent	-1.1	
41186	44	technician	married	professional.course	no	no	cellular	nov	fri	442	1	0	nonexistent	-1.1	
41187	74	retired	married	professional.course	yes	no	cellular	nov	fri	239	3	1	failure	-1.1	

38245 rows × 19 columns

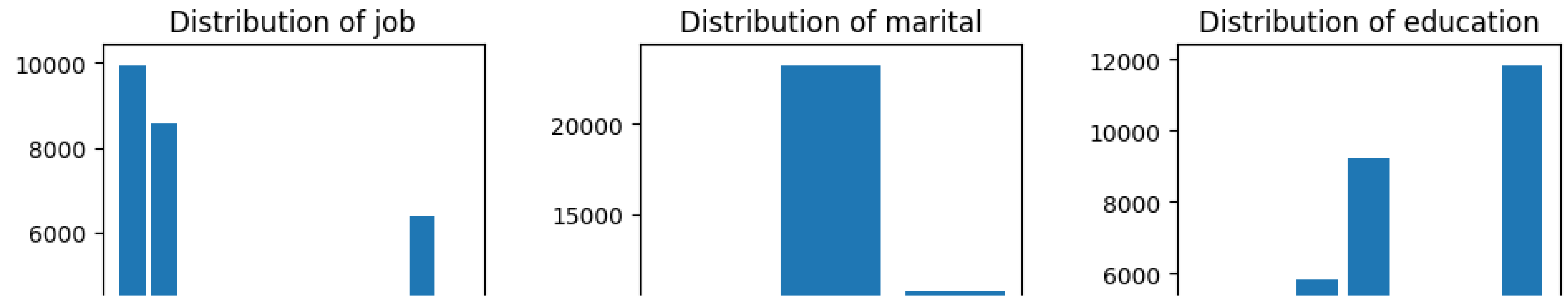
```
bank_add.groupby('job', as_index=False)['age'].count()
```

	job	age
0	admin.	9937
1	blue-collar	8560
2	entrepreneur	1360
3	housemaid	987
4	management	2728
5	retired	1577
6	self-employed	1349
7	services	3716
8	student	688
9	technician	6380
10	unemployed	963

```
categorical_variables
```

```
['job',
 'marital',
 'education',
 'housing',
 'loan',
 'contact',
 'month',
 'day_of_week',
 'poutcome']
```

```
fig, ax = plt.subplots(3,3, figsize=(10,10))
index = 0
for i in range(3):
  for j in range(3):
    t = bank_add.groupby(categorical_variables[index], as_index=False)['age'].count()
    ax[i,j].bar(t[categorical_variables[index]],t['age'])
    ax[i,j].set_title("Distribution of "+str(categorical_variables[index]))
    # ax[i,j].set_xlabel('Bins')
    index = index + 1
plt.tight_layout()
plt.show()
```




```
bank_add
```

	age	job	marital	education	housing	loan	contact	month	day_of_week	duration	campaign	previous	poutcome	emp.var.rate	cons.pric
0	56	housemaid	married	basic.4y	no	no	telephone	may	mon	261	1	0	nonexistent	1.1	
1	57	services	married	high.school	no	no	telephone	may	mon	149	1	0	nonexistent	1.1	
2	37	services	married	high.school	yes	no	telephone	may	mon	226	1	0	nonexistent	1.1	
3	40	admin.	married	basic.6y	no	no	telephone	may	mon	151	1	0	nonexistent	1.1	
4	56	services	married	high.school	no	yes	telephone	may	mon	307	1	0	nonexistent	1.1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
41183	73	retired	married	professional.course	yes	no	cellular	nov	fri	334	1	0	nonexistent	-1.1	
41184	46	blue-collar	married	professional.course	no	no	cellular	nov	fri	383	1	0	nonexistent	-1.1	
41185	56	retired	married	university.degree	yes	no	cellular	nov	fri	189	2	0	nonexistent	-1.1	
41186	44	technician	married	professional.course	no	no	cellular	nov	fri	442	1	0	nonexistent	-1.1	
41187	74	retired	married	professional.course	yes	no	cellular	nov	fri	239	3	1	failure	-1.1	

38245 rows × 19 columns

12000

```
categorical_variables
```

```
['job',
 'marital',
 'education',
 'housing',
 'loan',
 'contact',
 'month',
 'day_of_week',
 'poutcome']
```

```
# Label Encoding - for categorical variables
encoder_ = LabelEncoder()
```

```
bank_corr_check = bank_add.copy()
```

```
bank_corr_check['y'] = encoder_.fit_transform(bank_corr_check['y'])
```

```
# One hot encoding
one_hot_encoded = pd.get_dummies(bank_corr_check[['poutcome','marital','education']])
df_encoded = pd.concat([bank_corr_check,one_hot_encoded],axis=1)
df_encoded.drop(['poutcome','marital','education','job'],axis=1,inplace=True)
```

```
categorical_variables2 = df_encoded.columns[df_encoded.dtypes == 'object'].tolist()
```

```
for i in categorical_variables2:
  df_encoded[i] = encoder_.fit_transform(df_encoded[i])
```

```
df_encoded.columns
```

```
Index(['age', 'housing', 'loan', 'contact', 'month', 'day_of_week', 'duration',
       'campaign', 'previous', 'emp.var.rate', 'cons.price.idx',
       'cons.conf.idx', 'euribor3m', 'nr.employed', 'y', 'poutcome_failure',
       'poutcome_nonexistent', 'poutcome_success', 'marital_divorced',
       'marital_married', 'marital_single', 'education_basic.4y',
       'education_basic.6y', 'education_basic.9y', 'education_high.school',
       'education_illiterate', 'education_professional.course',
       'education_university.degree'],
      dtype='object')
```

```
df_encoded.drop(['day_of_week','month','duration'],axis=1,inplace=True)
```

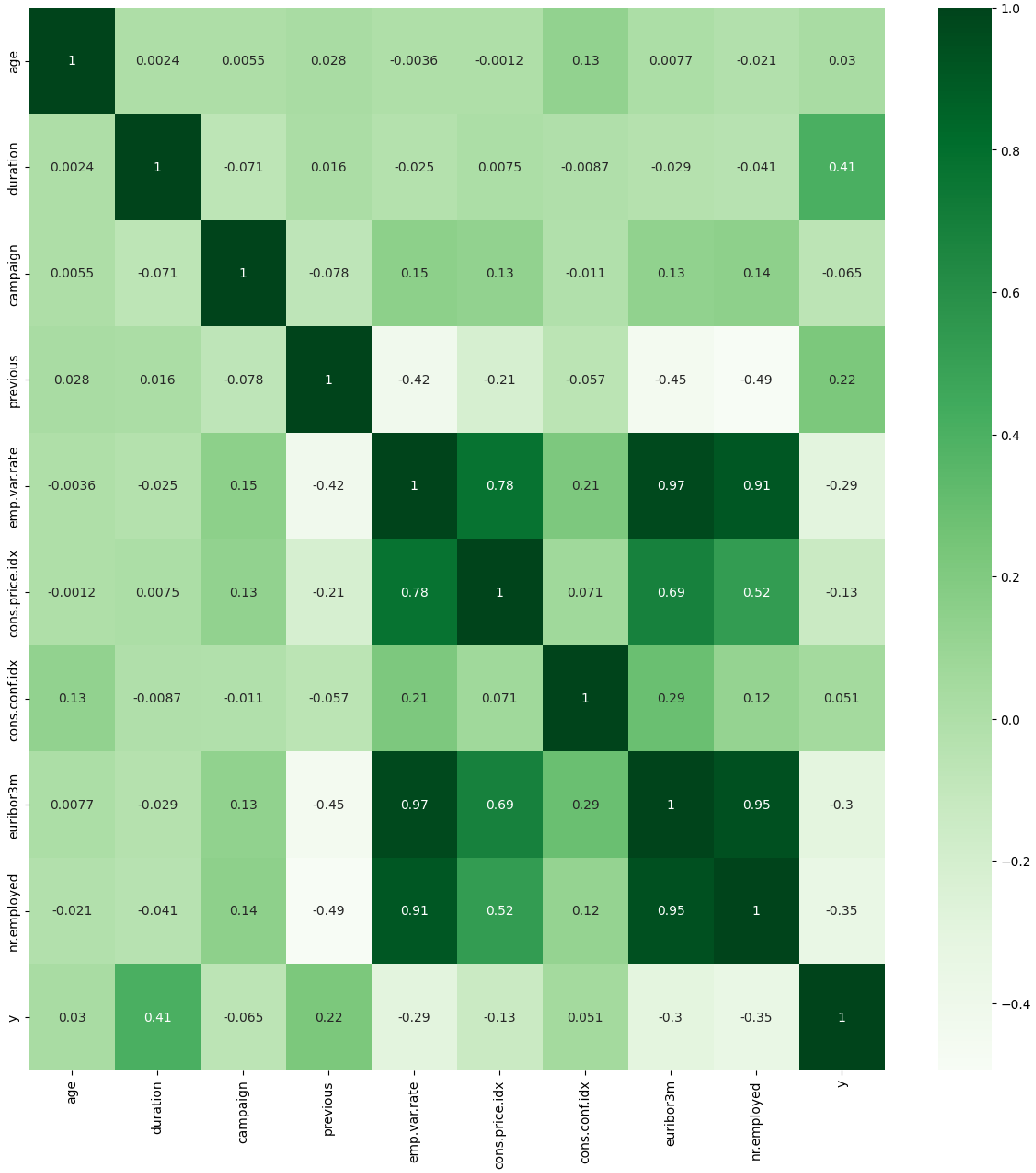
```
df_encoded
```

	age	housing	loan	contact	campaign	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed	y	poutcome_failure	poutcome_
0	56	0	0	1	1	0	1.1	93.994	-36.4	4.857	5191.0	0	0	
1	57	0	0	1	1	0	1.1	93.994	-36.4	4.857	5191.0	0	0	
2	37	1	0	1	1	0	1.1	93.994	-36.4	4.857	5191.0	0	0	
3	40	0	0	1	1	0	1.1	93.994	-36.4	4.857	5191.0	0	0	
4	56	0	1	1	1	0	1.1	93.994	-36.4	4.857	5191.0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
41183	73	1	0	0	1	0	-1.1	94.767	-50.8	1.028	4963.6	1	0	
41184	46	0	0	0	1	0	-1.1	94.767	-50.8	1.028	4963.6	0	0	
41185	56	1	0	0	2	0	-1.1	94.767	-50.8	1.028	4963.6	0	0	
41186	44	0	0	0	1	0	-1.1	94.767	-50.8	1.028	4963.6	1	0	
41187	74	1	0	0	3	1	-1.1	94.767	-50.8	1.028	4963.6	0	1	

38245 rows × 25 columns

```
# Correlation heatmap
fig, ax = plt.subplots(figsize=(15,15))
sns.heatmap(bank_corr_check.corr(),annot=True,cmap='Greens')
```

```
<ipython-input-71-4631aec7cfb5>:3: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will defau
  sns.heatmap(bank_corr_check.corr(),annot=True,cmap='Greens')
<Axes: >
```



```
# Getting a correlation matrix and getting all the columns which have 100% correlated with other
corr_= bank_corr_check.corr().abs() # getting the correlation matrix
upper = corr_.where(np.triu(np.ones(corr_.shape), k=1).astype(np.bool)) # making the lower traingle null
drop_col = [column for column in upper.columns if any(upper[column] >= 0.9)] # getting one of the columns to drop if they are same
```

```
<ipython-input-72-951b823455e3>:2: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select o
  corr_= bank_corr_check.corr().abs() # getting the correlation matrix
<ipython-input-72-951b823455e3>:3: DeprecationWarning: `np.bool` is a deprecated alias for the builtin `bool`. To silence this warning, use `bool` by itself. Doing this wil
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  upper = corr_.where(np.triu(np.ones(corr_.shape), k=1).astype(np.bool)) # making the lower traingle null
```

```
drop_col
```

```
['euribor3m', 'nr.employed']
```

```
drop_col = drop_col + ['duration']
```

```
bank_add = bank_add.drop(drop_col, axis = 1)
```

```
df_encoded
```

	age	housing	loan	contact	campaign	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed	y	poutcome_failure	poutcome_
0	56	0	0	1	1	0	1.1	93.994	-36.4	4.857	5191.0	0	0	
1	57	0	0	1	1	0	1.1	93.994	-36.4	4.857	5191.0	0	0	
2	37	1	0	1	1	0	1.1	93.994	-36.4	4.857	5191.0	0	0	
3	40	0	0	1	1	0	1.1	93.994	-36.4	4.857	5191.0	0	0	
4	56	0	1	1	1	0	1.1	93.994	-36.4	4.857	5191.0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	

Model building and Performance evaluation

```
X = df_encoded.drop(['y'],axis=1)
y = df_encoded['y'].values.reshape(-1, 1)
```

```
x_train,x_test,y_train,y_test = train_test_split(X,y,test_size=0.25,random_state=32)
```

Model 1 - Logistic Regression

```
logistic_regression = LogisticRegression()
```

```
logistic_regression.fit(x_train,y_train)
```

```
/usr/local/lib/python3.9/dist-packages/sklearn/utils/validation.py:1143: DataConversionWarning: A column-vector y was passed when a 1d array was expect
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_logistic.py:458: 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()
```

```
y_pred1 = logistic_regression.predict(x_test)
```

```
accuracy1 = accuracy_score(y_test,y_pred1)
accuracy1
```

```
0.8935369169629784
```

```
accuracy1 = accuracy_score(y_test,y_pred1)
precision1 = precision_score(y_test,y_pred1)
recall1 = recall_score(y_test,y_pred1)
print(f"ACCURACY for Logistic Regression:{accuracy1:.3f}")
print(f"Precision :{precision1:.3f} and Recall : {recall1:.3f}")
```

```
ACCURACY for Logistic Regression:0.894
Precision :0.552 and Recall : 0.241
```

```
#MAE
mae = mean_absolute_error(y_test,y_pred1)
print(f"MAE for Logistic Regression: {mae:.3f}")

# Root Mean Squared Error (RMSE)
rmse = np.sqrt(mean_squared_error(y_test,y_pred1))
print(f"RMSE for Logistic Regression:{rmse:.3f}")
```

```
MAE for Logistic Regression: 0.106
RMSE for Logistic Regression:0.326
```

```
confusion_matrix1 = confusion_matrix(y_test,y_pred1)
```

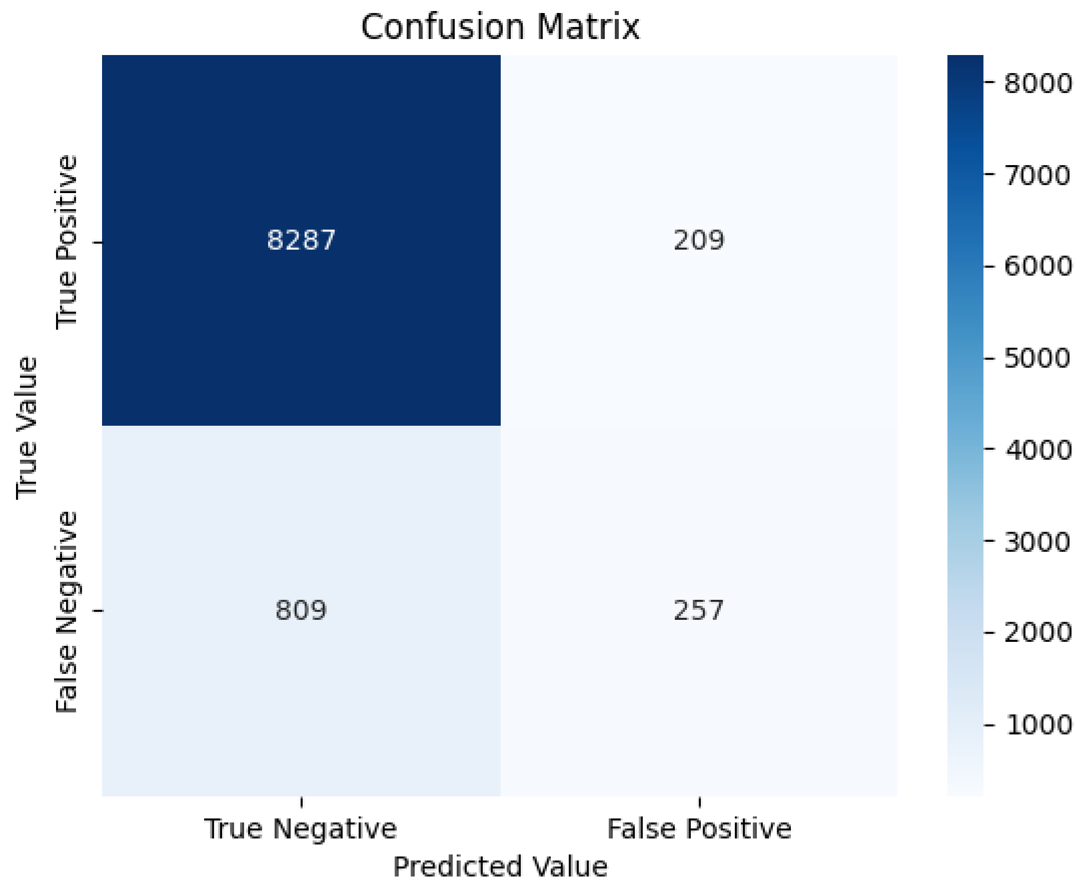
```
cm = confusion_matrix(y_test,y_pred1)
```

```
confusion_matrix1
```

```
array([[8287,  209],
       [ 809,  257]])
```

```
xlabels = ['True Negative', 'False Positive']
ylabels = ['True Positive', 'False Negative']
```

```
# Reshape the confusion matrix to a 1D array
cm_1d = cm.ravel()

# Convert the counts to strings without scientific notation and no decimal places
cm_1d_str = [f'{count:.0f}' for count in cm_1d]

# Reshape the string array back to its original shape
cm_annot = np.array(cm_1d_str).reshape((2, 2))

# Create a heatmap visualization of the confusion matrix with count annotations
sns.heatmap(cm, annot=cm_annot, fmt='', cmap='Blues', xticklabels=xlabels, yticklabels=ylabels)

# Set the axis labels and plot title
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.title('Confusion Matrix')

# Show the plot
plt.show()
```




```
fpr,tpr,threshold = metrics.roc_curve(y_test,y_pred1)
```

```
auc1 = metrics.auc(fpr,tpr)
```

Model 2 - Support Vector Machine

```
SVM = SVC(kernel='linear')
```

```
SVM.fit(x_train,y_train)
```

```
/usr/local/lib/python3.9/dist-packages/sklearn/utils/validation.py:1143: DataConversionWarning: A column-vector y was passed when a 1d array was expect
  y = column_or_1d(y, warn=True)
▾      SVC
SVC(kernel='linear')
```

```
y_pred2 = SVM.predict(x_test)
```

```
accuracy2 = accuracy_score(y_test,y_pred2)
precision2 = precision_score(y_test,y_pred2)
recall2 = recall_score(y_test,y_pred2)
print(f"ACCURACY for SVM:{accuracy2:.3f}")
print(f"Precision :{precision2:.3f} and Recall : {recall2:.3f}")
```

```
ACCURACY for SVM:0.898
Precision :0.711 and Recall : 0.136
```

```
#MAE
mae = mean_absolute_error(y_test,y_pred2)
print(f"MAE for Support Vector Machine model: {mae:.3f}")

# Root Mean Squared Error (RMSE)
rmse = np.sqrt(mean_squared_error(y_test,y_pred2))
print(f"RMSE for Support Vector Machine model:{rmse:.3f}")
```

```
MAE for Support Vector Machine model: 0.102
RMSE for Support Vector Machine model:0.320
```

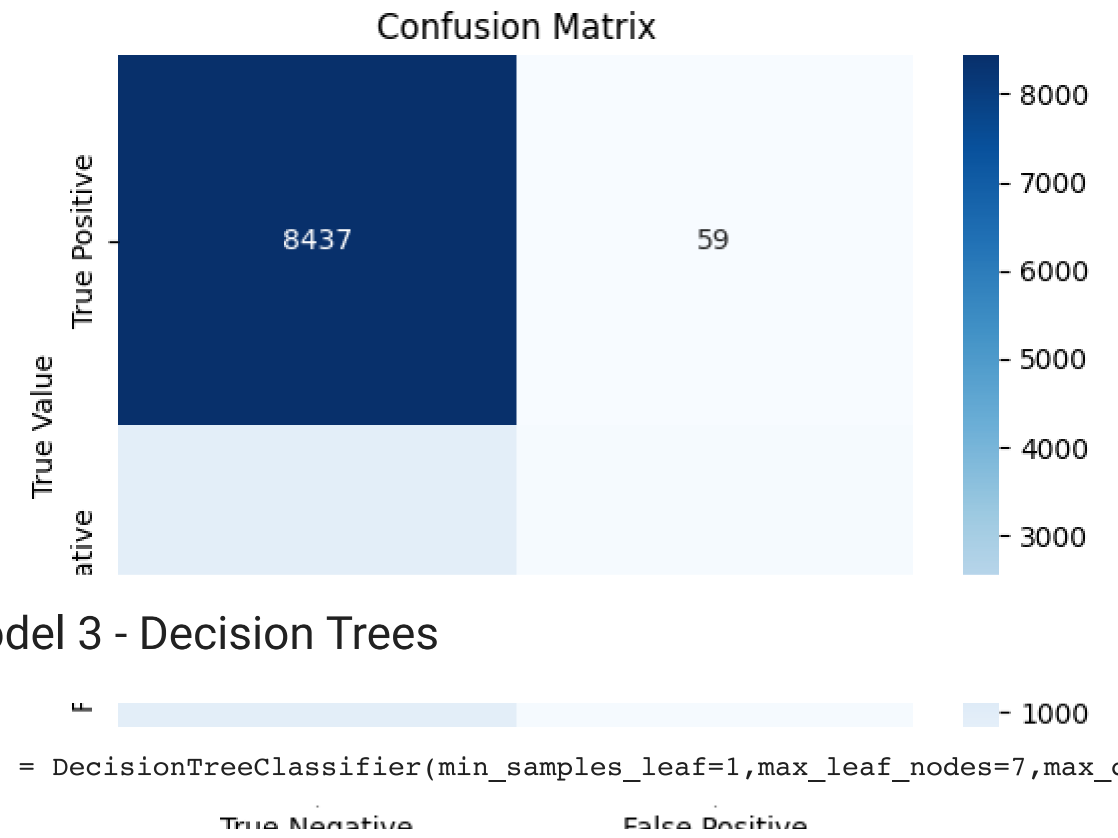
```
cm2 = confusion_matrix(y_test,y_pred2)
```

```
cm2
```

```
array([[8437,   59],
       [ 921,  145]])
```

```
xlabels = ['True Negative', 'False Positive']
ylabels = ['True Positive', 'False Negative']
```

```
# Reshape the confusion matrix to a 1D array
cm_1d = cm2.ravel()

# Convert the counts to strings without scientific notation and no decimal places
cm_1d_str = [f'{count:.0f}' for count in cm_1d]

# Reshape the string array back to its original shape
cm_annot = np.array(cm_1d_str).reshape((2, 2))

# Create a heatmap visualization of the confusion matrix with count annotations
sns.heatmap(cm2, annot=cm_annot, fmt='', cmap='Blues', xticklabels=xlabels, yticklabels=ylabels)

# Set the axis labels and plot title
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.title('Confusion Matrix')

# Show the plot
plt.show()
```



Model 3 - Decision Trees

```
Tree = DecisionTreeClassifier(min_samples_leaf=1,max_leaf_nodes=7,max_depth=3)
```

```
parameter_grid = {'max_depth': [2, 3, 4, 5,6,7], 'min_samples_leaf': [1, 2, 3,4,5], 'max_leaf_nodes': [2,3, 4, 5, 6,7] }
```

```
grid_search = GridSearchCV(Tree, parameter_grid, cv=5)
grid_search.fit(x_train, y_train)
```

```
▸ GridSearchCV
▸ estimator: DecisionTreeClassifier
  ▸ DecisionTreeClassifier
```

```
best_params = grid_search.best_params_
print('Best hyperparameters:', best_params)
```

```
Best hyperparameters: {'max_depth': 2, 'max_leaf_nodes': 3, 'min_samples_leaf': 1}
```

```
Tree.fit(x_train,y_train)
```

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(max_depth=3, max_leaf_nodes=7)
```

```
y_pred3 = Tree.predict(x_test)
```

```
accuracy3 = accuracy_score(y_test,y_pred3)
precision3 = precision_score(y_test,y_pred3)
recall3 = recall_score(y_test,y_pred3)
print(f"ACCURACY for Decision Trees:{accuracy3:.3f}")
print(f"Precision :{precision3:.3f} and Recall : {recall3:.3f}")
```

```
ACCURACY for Decision Trees:0.902
Precision :0.745 and Recall : 0.187
```

```
#MAE
mae = mean_absolute_error(y_test,y_pred3)
print(f"MAE for Decision Trees model: {mae:.3f}")

# Root Mean Squared Error (RMSE)
rmse = np.sqrt(mean_squared_error(y_test,y_pred3))
print(f"RMSE for Decision Trees model: {rmse:.3f}")
```

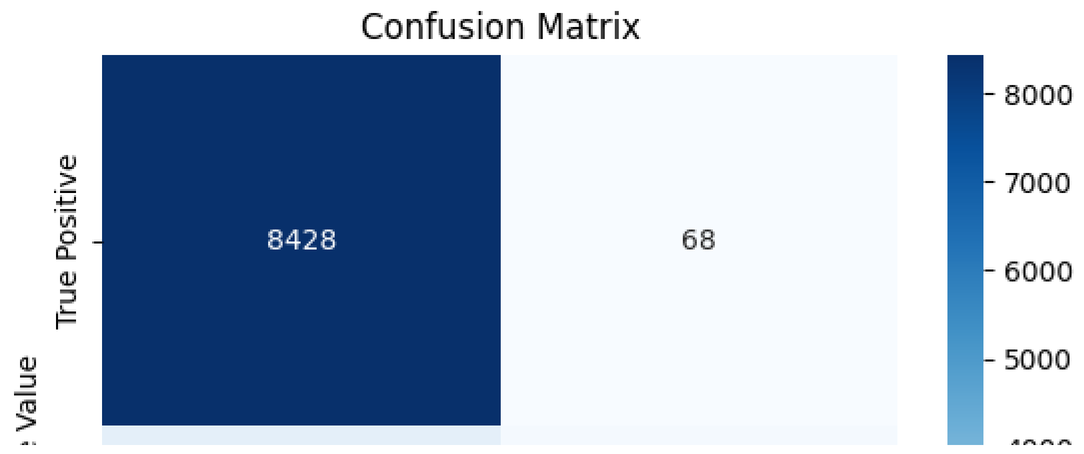
```
MAE for Decision Trees model: 0.098
RMSE for Decision Trees model: 0.313
```

```
cm3 = confusion_matrix(y_test,y_pred3)
```

```
cm3
```

```
array([[8428,   68],
       [ 867,  199]])
```

```
# Reshape the confusion matrix to a 1D array
cm_1d = cm3.ravel()

# Convert the counts to strings without scientific notation and no decimal places
cm_1d_str = [f'{count:.0f}' for count in cm_1d]

# Reshape the string array back to its original shape
cm_annot = np.array(cm_1d_str).reshape((2, 2))

# Create a heatmap visualization of the confusion matrix with count annotations
sns.heatmap(cm3, annot=cm_annot, fmt='', cmap='Blues', xticklabels=xlabels, yticklabels=ylabels)

# Set the axis labels and plot title
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.title('Confusion Matrix')

# Show the plot
plt.show()
```



Model 4 - Gradient Boosting

```
GradientBoosting = GradientBoostingClassifier()
```

```
GradientBoosting.fit(x_train,y_train)
```

```
/usr/local/lib/python3.9/dist-packages/sklearn/ensemble/_gb.py:437: DataConversionWarning: A column-vector y was passed when a 1d array was expected.
  y = column_or_1d(y, warn=True)
▾ GradientBoostingClassifier
GradientBoostingClassifier()
```

```
y_pred4 = GradientBoosting.predict(x_test)
```

```
accuracy4 = accuracy_score(y_test,y_pred4)
precision4 = precision_score(y_test,y_pred4)
recall4 = recall_score(y_test,y_pred4)
print(f"ACCURACY for Gradient Boosting:{accuracy4:.3f}")
print(f"Precision :{precision4:.3f} and Recall : {recall4:.3f}")
```

```
ACCURACY for Gradient Boosting:0.902
Precision :0.657 and Recall : 0.259
```

```
#MAE
mae = mean_absolute_error(y_test,y_pred4)
print(f"MAE for Gradient Boosting model: {mae:.3f}")

# Root Mean Squared Error (RMSE)
rmse = np.sqrt(mean_squared_error(y_test,y_pred4))
print(f"RMSE for Gradient Boosting model: {rmse:.3f}")
```

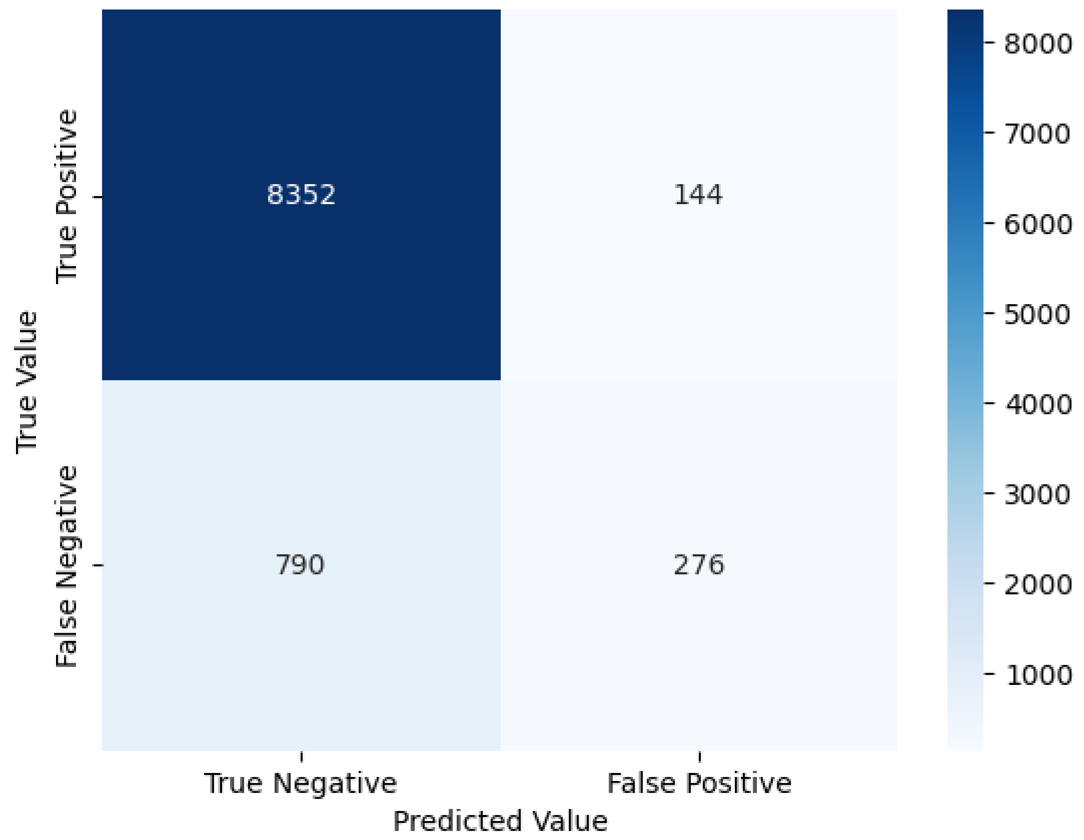
```
MAE for Gradient Boosting model: 0.098
RMSE for Gradient Boosting model: 0.313
```

```
cm4 = confusion_matrix(y_test,y_pred4)
```

```
cm4
```

```
array([[8352,  144],
       [ 790,  276]])
```

```
# Reshape the confusion matrix to a 1D array
cm_1d = cm4.ravel()

# Convert the counts to strings without scientific notation and no decimal places
cm_1d_str = [f'{count:.0f}' for count in cm_1d]

# Reshape the string array back to its original shape
cm_annot = np.array(cm_1d_str).reshape((2, 2))

# Create a heatmap visualization of the confusion matrix with count annotations
sns.heatmap(cm4, annot=cm_annot, fmt='', cmap='Blues', xticklabels=xlabels, yticklabels=ylabels)

# Set the axis labels and plot title
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.title('Confusion Matrix')

# Show the plot
plt.show()
```



Model-5 Random Forest

```
random_forest = RandomForestClassifier(n_estimators=100, random_state=42, max_depth=15, min_samples_split=5, min_samples_leaf=2, max_features=0.5)
```

```
random_forest.fit(x_train,y_train)
```

```
<ipython-input-122-6f391acbaaaf>:1: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to
  random_forest.fit(x_train,y_train)
▾                          RandomForestClassifier
RandomForestClassifier(max_depth=15, max_features=0.5, min_samples_leaf=2,
                       min_samples_split=5, random_state=42)
```

```
y_pred5 = random_forest.predict(x_test)
```

```
accuracy5 = accuracy_score(y_test,y_pred5)
precision5 = precision_score(y_test,y_pred5)
recall5 = recall_score(y_test,y_pred5)
print(f"ACCURACY for random forest:{accuracy5:.3f}")
print(f"Precision :{precision5:.3f} and Recall : {recall5:.3f}")
```

```
ACCURACY for random forest:0.900
Precision :0.610 and Recall : 0.286
```

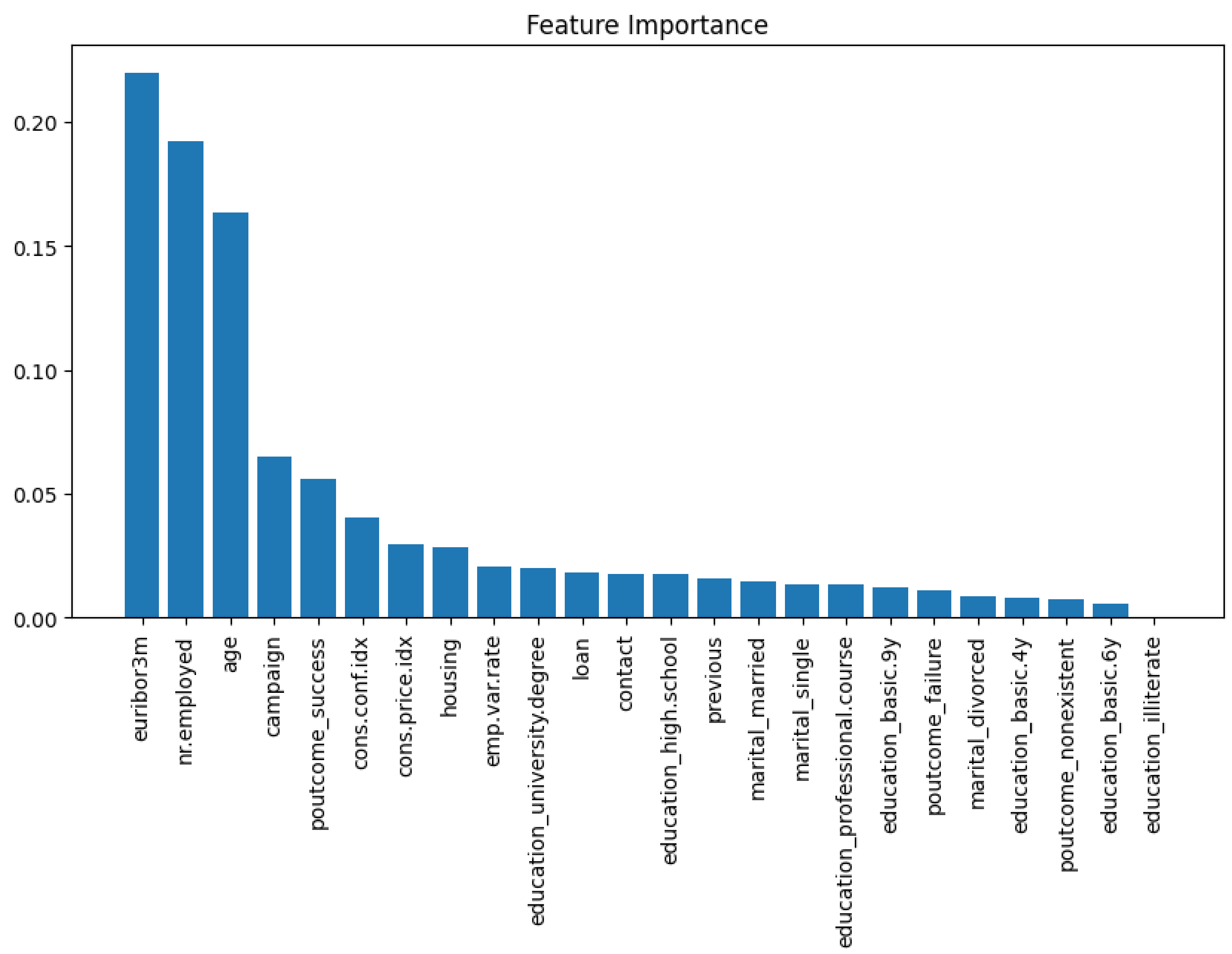
```
y_predx = random_forest.predict(x_train)
acc = accuracy_score(y_train,y_predx)
```

```
acc
```

```
0.9363037339190461
```

```
importances = random_forest.feature_importances_
indices = np.argsort(importances)[::-1]
```

```
plt.figure(figsize=(10,5))
plt.title("Feature Importance")
plt.bar(range(X.shape[1]), importances[indices])
plt.xticks(range(X.shape[1]), X.columns[indices], rotation=90)
plt.show()
```




```
df_encoded.columns
```

```
Index(['age', 'housing', 'loan', 'contact', 'campaign', 'previous',
       'emp.var.rate', 'cons.price.idx', 'cons.conf.idx', 'euribor3m',
       'nr.employed', 'y', 'poutcome_failure', 'poutcome_nonexistent',
       'poutcome_success', 'marital_divorced', 'marital_married',
       'marital_single', 'education_basic.4y', 'education_basic.6y',
       'education_basic.9y', 'education_high.school', 'education_illiterate',
       'education_professional.course', 'education_university.degree'],
      dtype='object')
```

```
new_df = df_encoded[['age','cons.price.idx','cons.conf.idx','poutcome_success','emp.var.rate','campaign',
                     'previous','housing','contact','poutcome_failure',
                     'loan','contact','y']]
```

```
X1 = new_df.drop(['y'],axis=1)
y1 = new_df['y'].values.reshape(-1, 1)
```

```
x_train1,x_test1,y_train1,y_test1 = train_test_split(X1,y1,test_size=0.25,random_state=32)
```

```
random_forest.fit(x_train1,y_train1)
```

```
<ipython-input-132-6055b54ad1e4>:1: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to
  random_forest.fit(x_train1,y_train1)
▾                          RandomForestClassifier
RandomForestClassifier(max_depth=15, max_features=0.5, min_samples_leaf=2,
                       min_samples_split=5, random_state=42)
```

```
y_pred6 = random_forest.predict(x_test1)
```

```
accuracy5 = accuracy_score(y_test,y_pred6)
precision5 = precision_score(y_test,y_pred6)
```

```
recall5 = recall_score(y_test,y_pred6)
print(f"ACCURACY for Random Forest:{accuracy5:.3f}")
print(f"Precision :{precision5:.3f} and Recall : {recall5:.3f}")
```

```
ACCURACY for Random Forest:0.899
Precision :0.598 and Recall : 0.277
```

```
#MAE
mae = mean_absolute_error(y_test,y_pred6)
print(f"MAE for Random Forest model: {mae:.3f}")

# Root Mean Squared Error (RMSE)
rmse = np.sqrt(mean_squared_error(y_test,y_pred6))
print(f"RMSE for Random Forest model: {rmse:.3f}")
```

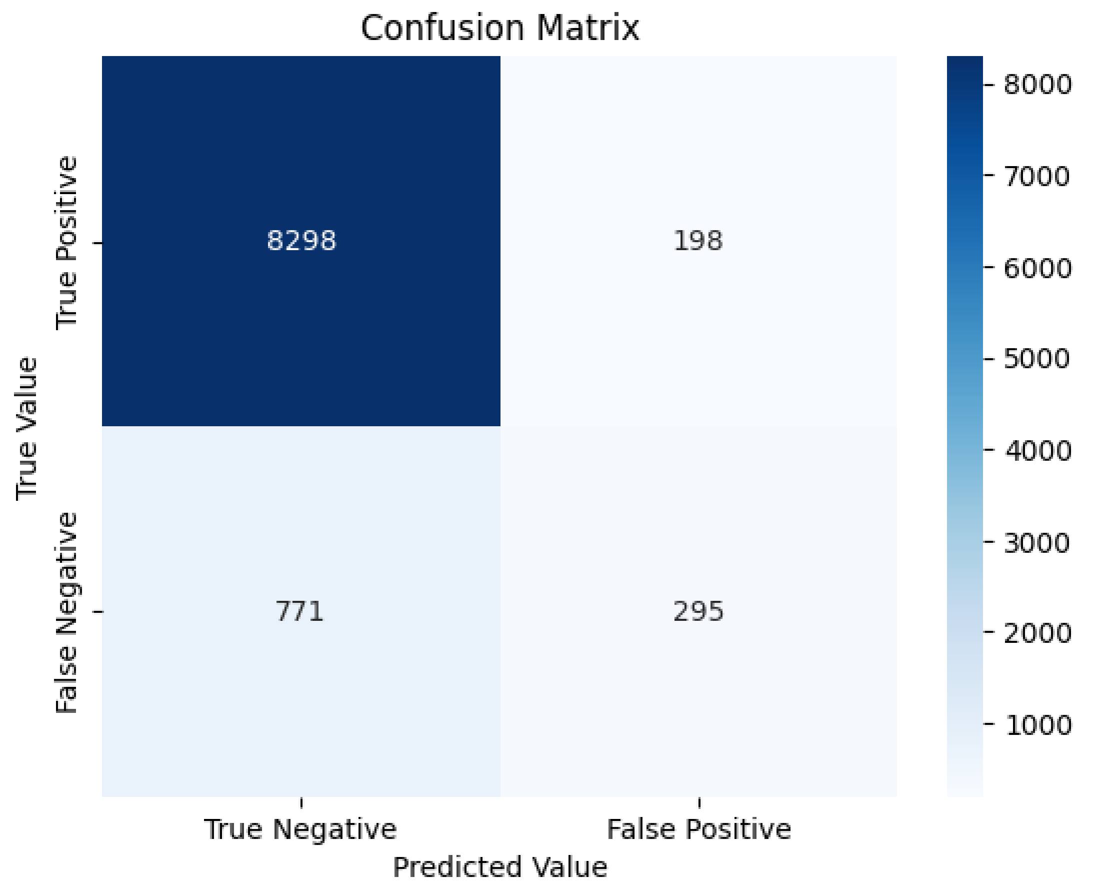
```
MAE for Random Forest model: 0.101
RMSE for Random Forest model: 0.318
```

```
cm5 = confusion_matrix(y_test,y_pred6)
```

```
cm5
```

```
array([[8298,  198],
       [ 771,  295]])
```

```
# Reshape the confusion matrix to a 1D array
cm_1d = cm5.ravel()

# Convert the counts to strings without scientific notation and no decimal places
cm_1d_str = [f'{count:.0f}' for count in cm_1d]

# Reshape the string array back to its original shape
cm_annot = np.array(cm_1d_str).reshape((2, 2))

# Create a heatmap visualization of the confusion matrix with count annotations
sns.heatmap(cm5, annot=cm_annot, fmt='', cmap='Blues', xticklabels=xlabels, yticklabels=ylabels)

# Set the axis labels and plot title
plt.xlabel('Predicted Value')
plt.ylabel('True Value')
plt.title('Confusion Matrix')

# Show the plot
plt.show()
```



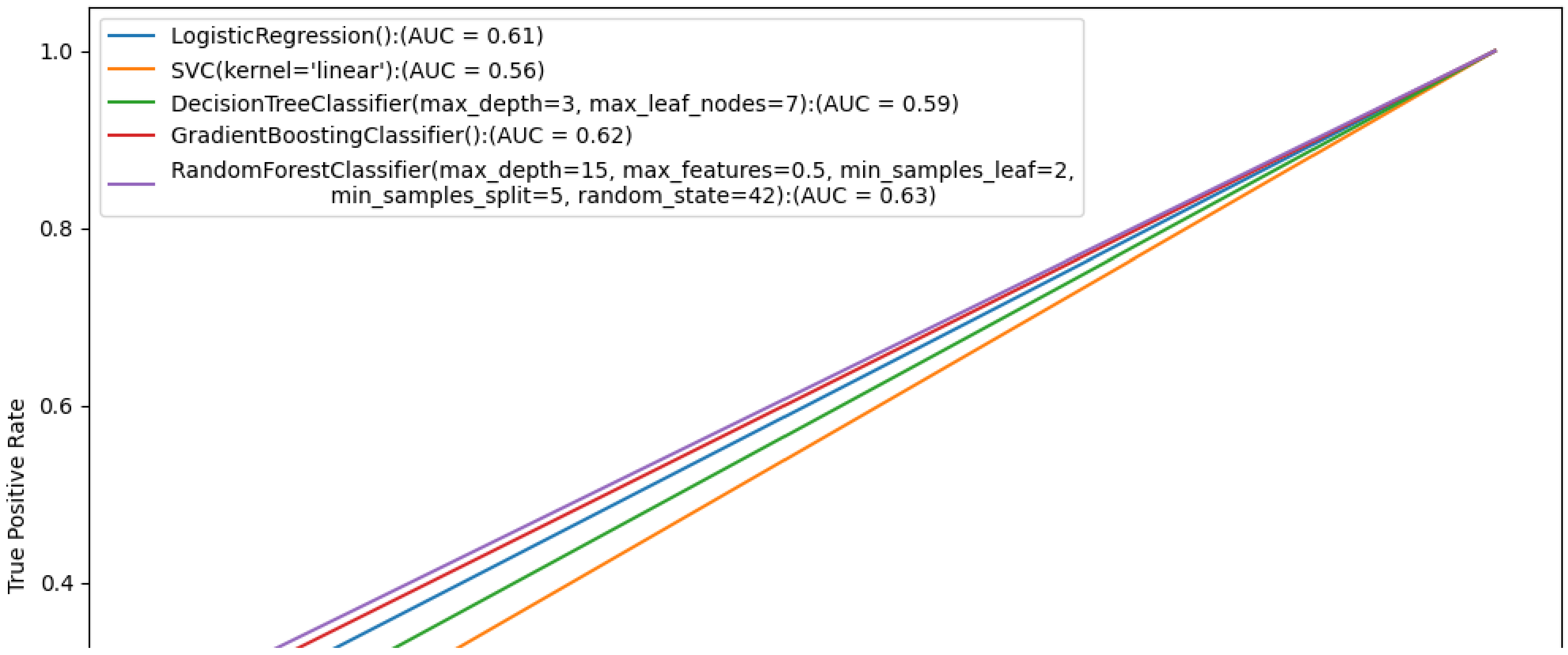

```
y_pred7 = random_forest.predict(x_train1)
accuracy7 = accuracy_score(y_train,y_pred7)
accuracy7
```

```
0.926576717916536
```

Performance Evaluation

```
models = [logistic_regression, SVM, Tree, GradientBoosting,random_forest]
y_pred = [y_pred1,y_pred2,y_pred3,y_pred4,y_pred6]
plt.figure(figsize=(12,8))
aucs=[]
for i,model in enumerate(models):
  y_predx = y_pred[i]
  fpr,tpr,threshold = metrics.roc_curve(y_test,y_predx)
  auc = metrics.auc(fpr,tpr)
  plt.plot(fpr, tpr, label=f"{model}:(AUC = {auc:.2f})")
  aucs.append(auc)
plt.legend()
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
```

```
Text(0, 0.5, 'True Positive Rate')
```




```
Accuracy = []
Precision = []
recall = []
for i in range(1,6):
  acc = eval(f"accuracy{i}")
  prc = eval(f"precision{i}")
  rc = eval(f"recall{i}")
  Accuracy.append(acc)
  Precision.append(prc)
  recall.append(rc)
```

```
Accuracy
```

```
[0.8935369169629784,
 0.8975109809663251,
 0.9022171093913407,
 0.9023216900230078,
 0.8986613679146622]
```

```
recall
```

```
[0.24108818011257035,
 0.13602251407129456,
 0.18667917448405252,
 0.2589118198874296,
 0.2767354596622889]
```

```
models1= ['Logistic Regression','SVM','Decision Tree Classifier','Gradient Boost','Random Forest']
```

```
data = {'Models': models1, 'Accuracy': Accuracy, 'Precision': Precision, 'recall': recall}
df = pd.DataFrame(data)
```

```
df
```

	Models	Accuracy	Precision	recall
0	Logistic Regression	0.893537	0.551502	0.241088
1	SVM	0.897511	0.710784	0.136023
2	Decision Tree Classifier	0.902217	0.745318	0.186679
3	Gradient Boost	0.902322	0.657143	0.258912
4	Random Forest	0.898661	0.598377	0.276735

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