MLSC - Classification Excercise

Program Offered: M. Tech / Data Science

Course Title: Machine Learning Supervised Classification (MLSC)

Group Number: 5

Name of the Project Members

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About the data set (Bank Client Data)

Bank client data:

age: Age of the client
duration: last contact duration, in seconds.

Other attributes:

campaign: number of contacts performed during this campaign and for this client
pdays: number of days that passed by after the client was last contacted from a previous campaign (999 means client was not previously contacted)
previous: number of contacts performed before this campaign and for this client

Social and economic context

emp.var.rate: employment variation rate - quarterly indicator
cons.price.idx: consumer price index - monthly indicator
cons.conf.idx: consumer confidence index - monthly indicator
euribor3m: euribor 3 month rate - daily indicator
nr.employed: number of employees - quarterly indicator

y - (Output variable) has the client subscribed a term deposit?

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1. Data Pre-Processing

Import the required libraries

In [1]:
```
# pip install xgboost
```

In [2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
import warnings
warnings.filterwarnings('ignore')
from sklearn.preprocessing import StandardScaler, MinMaxScaler

from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB, BernoulliNB, MultinomialNB


from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, confusion_matrix, cohen_kappa_score,log_loss
from sklearn.metrics import precision_score, recall_score, f1_score, classification_report,auc, roc_curve,roc_auc_score
```

Load the csv file

In [3]:
```
df = pd.read_csv('bank.csv')
```

Prepare the data

In [4]:
```
print(df.info())
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9640 entries, 0 to 9639
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   age             9640 non-null   int64  
 1   duration        9640 non-null   int64  
 2   campaign        9640 non-null   int64  
 3   pdays           9640 non-null   int64  
 4   previous        9640 non-null   int64  
 5   emp.var.rate    9640 non-null   float64
 6   cons.price.idx  9640 non-null   float64
 7   cons.conf.idx   9640 non-null   float64
 8   euribor3m       9640 non-null   float64
 9   nr.employed     9640 non-null   float64
 10  y               9640 non-null   object 
dtypes: float64(5), int64(5), object(1)
memory usage: 828.6+ KB
None
```

Out[4]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed	y
0	32	205	2	999	0	1.1	93.994	-36.4	4.858	5191.0	no
1	32	691	10	999	0	1.4	93.918	-42.7	4.960	5228.1	yes
2	45	45	8	999	0	1.4	93.444	-36.1	4.963	5228.1	no
3	33	400	1	5	2	-1.1	94.601	-49.5	1.032	4963.6	yes
4	47	903	2	999	1	-1.8	93.075	-47.1	1.415	5099.1	yes

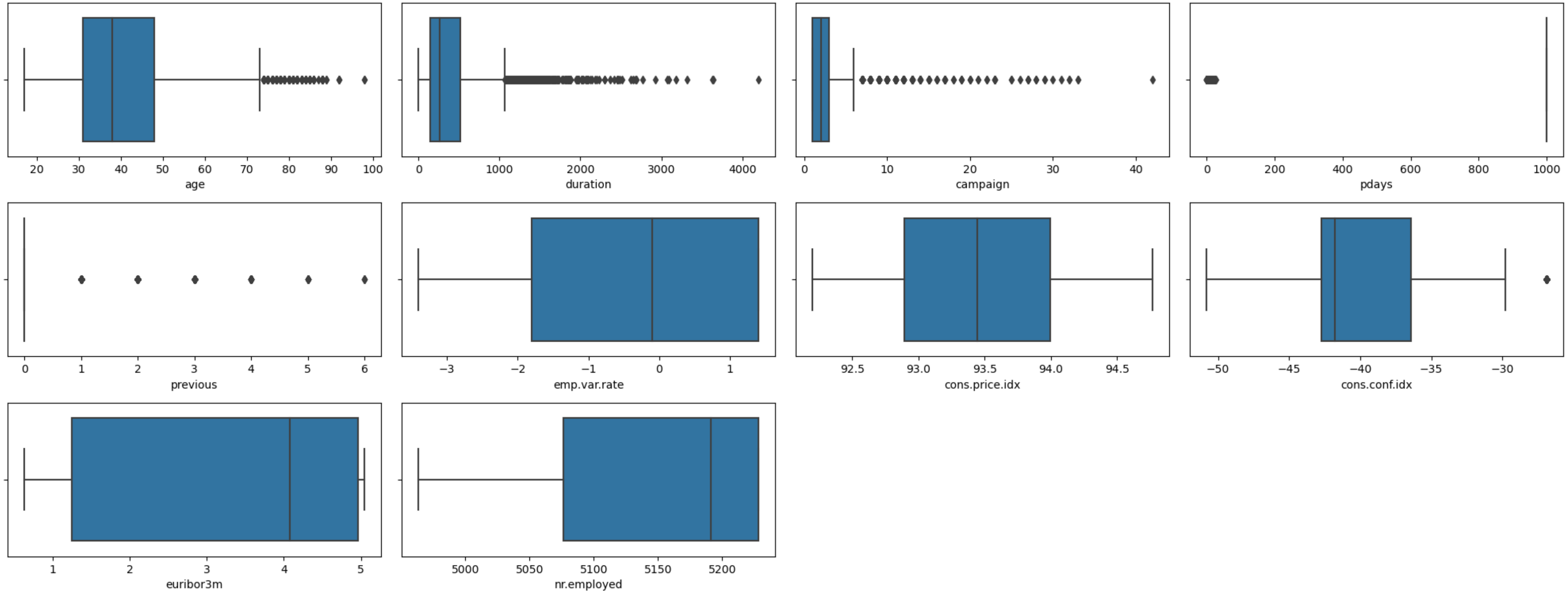
Perform an analysis for missing values

In [5]:
```
df.isnull().sum()
```

Out[5]:
```
age               0
duration          0
campaign          0
pdays             0
previous          0
emp.var.rate      0
cons.price.idx    0
cons.conf.idx     0
euribor3m         0
nr.employed       0
y                 0
dtype: int64
```

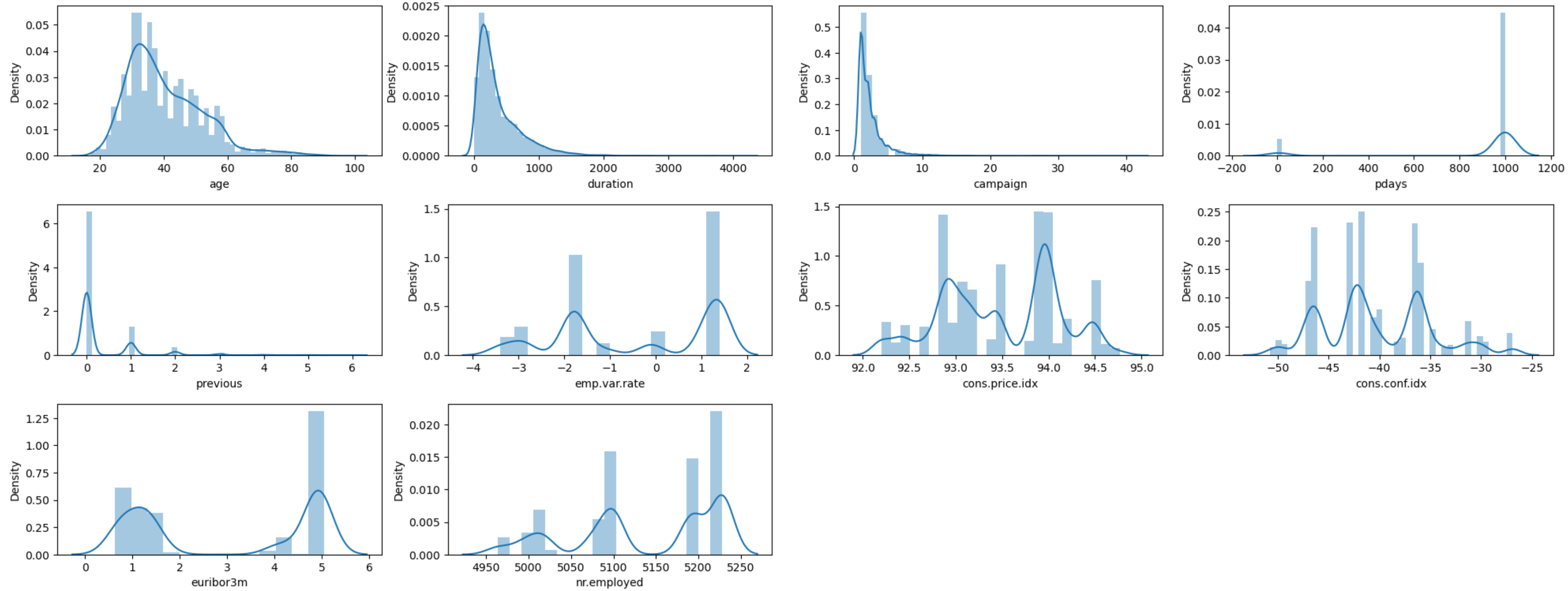
Remove the outliers (if any)

In [6]:
```python
plt.figure(figsize=(20,30))
for i, col in enumerate(df.select_dtypes(exclude='object').columns):
    plt.subplot(round(len(df.columns))+1,4,i+1)
    sns.boxplot(df[col])
plt.tight_layout()
```



In [7]:

```
plt.figure(figsize=(20,30))
for i, col in enumerate(df.select_dtypes(exclude='object').columns):
    plt.subplot(round(len(df.columns))+1,4,i+1)
    sns.distplot(df[col])
plt.tight_layout()
```



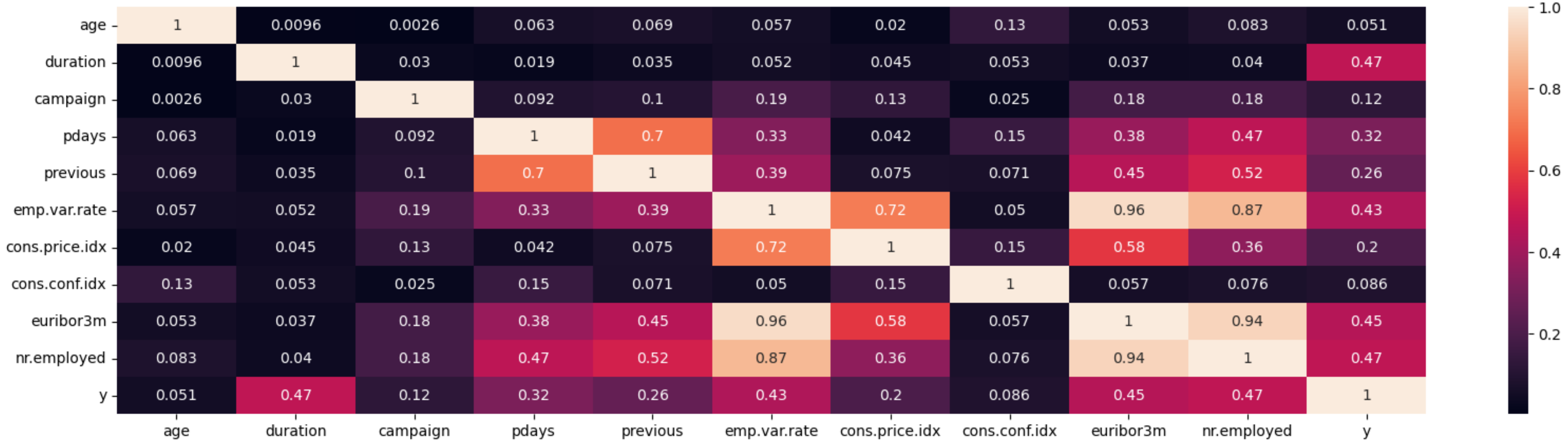
INFERENCE: **As per requesties the datas are loaded using the pandas library and checked with missing values. Here there is no missing values , so its been contitued with outlier detectinn**

Separate the dependent and the independent variables. Also, in the target variable, replace yes with 0 and no with 1

In [8]:

```
df['y'].replace(['yes','no'],[0,1],inplace=True)
depVar = df.drop(columns='y')
indepVar = df['y']
```

In [9]:
```
plt.figure(figsize=(20,5))
sns.heatmap(abs(df.corr()), annot=True)
```
Out[9]: <AxesSubplot:>



Remove the unnecessary variables that will not contribute to the model.

In [10]:
```
# droping 'age' as per corelation value with respect to independent variable
depVar.drop(columns=['age'], inplace=True)
```

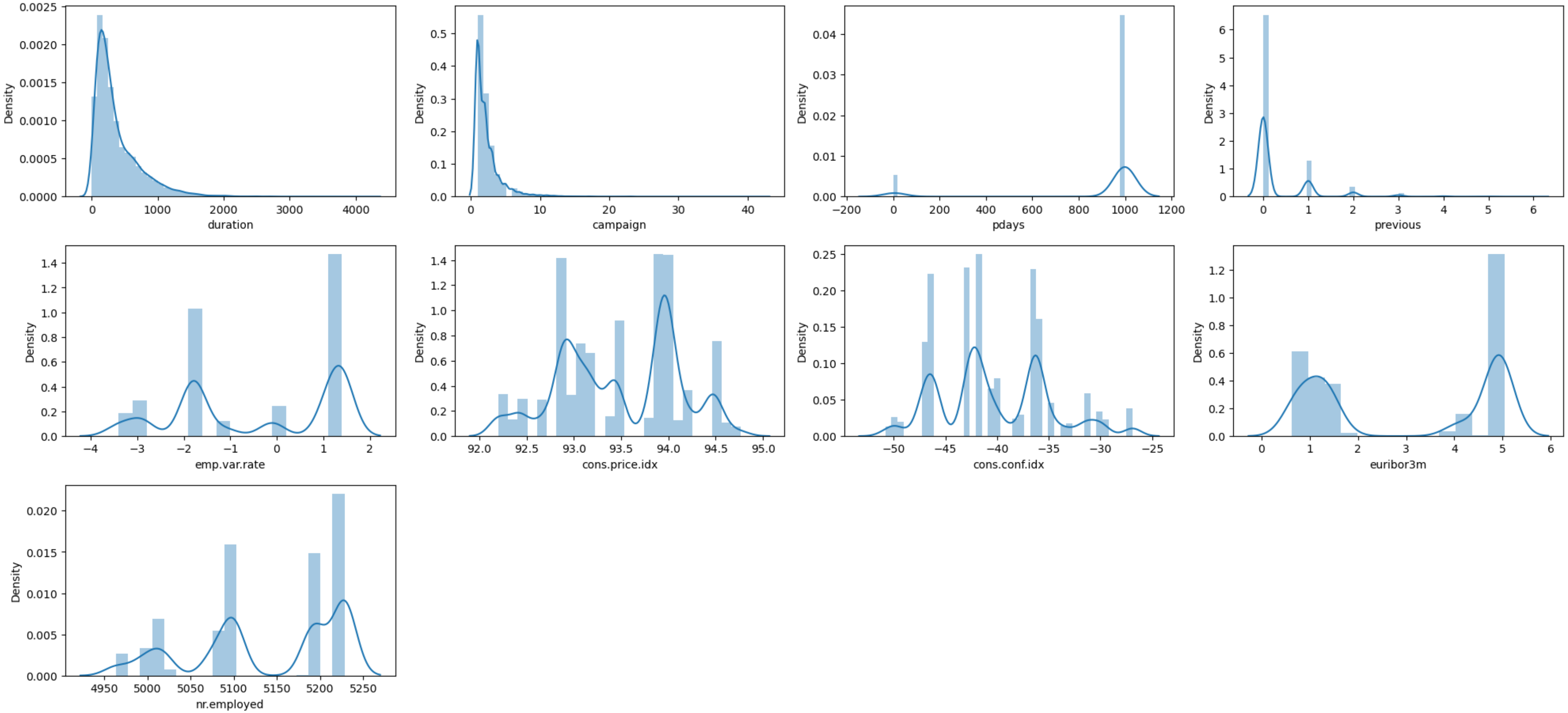
Plot the distribution of all the numeric variables and find the value of skewness for each variable.

In [11]:
```
skewness = pd.DataFrame(depVar.skew(axis=0), columns=['Skewness'])
skewness
```

Out[11]:

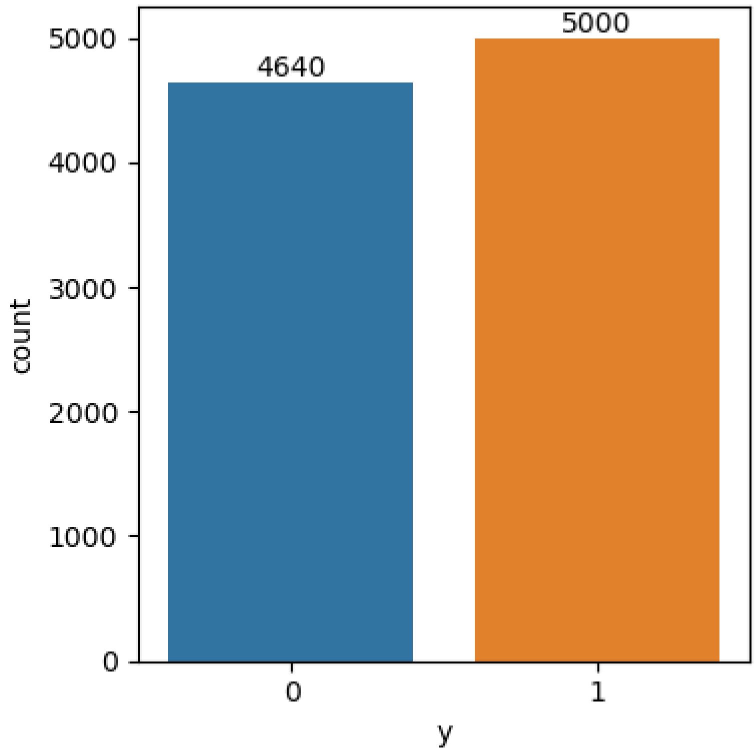
	Skewness
duration	2.256322
campaign	5.098841
pdays	-2.549356
previous	2.895599
emp.var.rate	-0.181234
cons.price.idx	-0.125216
cons.conf.idx	0.350442
euribor3m	-0.058332
nr.employed	-0.463581

In [12]:
```python
plt.figure(figsize=(20,30))
for i, col in enumerate(depVar.columns):
    plt.subplot(round(len(depVar.columns))+1,4,i+1)
    sns.distplot(depVar[col])
plt.tight_layout()
plt.show()
```



Plot the distribution of the target variable.

In [13]:
```
plt.figure(figsize=(4,4))
ax = sns.countplot(indepVar)
ax.bar_label(ax.containers[0])
plt.tight_layout()
plt.show()
```



Scale all the numeric variables using standard scalar.

In [14]:
```
scaler = StandardScaler()
temp = scaler.fit_transform(depVar)
depVar = pd.DataFrame(temp, columns=depVar.columns)
depVar.head()
```

Out[14]:

	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
0	-0.492076	-0.146440	0.345494	-0.447172	0.908285	0.805042	0.726230	0.983194	0.620697
1	0.877903	3.208708	0.345494	-0.447172	1.082931	0.684662	-0.457420	1.037275	1.050379
2	-0.943098	2.369921	0.345494	-0.447172	1.082931	-0.066130	0.782594	1.038865	1.050379
3	0.057607	-0.565833	-2.897406	2.474374	-0.372451	1.766500	-1.735011	-1.045350	-2.012985
4	1.475507	-0.146440	0.345494	1.013601	-0.779958	-0.650607	-1.284096	-0.842284	-0.443662

User Defined Model Function

In [15]:
```
def model_func(model, X_train, y_train, X_test):
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    # Calculating precision
    precision = precision_score(y_test, y_pred)
    # Calculating recall
    recall = recall_score(y_test, y_pred)
    # Calculating F1 score
    f1 = f1_score(y_test, y_pred)
    # Calculating Accuracy score
    accuracy = accuracy_score(y_test, y_pred)
    fpr, tpr, thresholds = roc_curve(y_test, y_pred)
    cross_entropy = log_loss(y_test, y_pred)
    roc_score = roc_auc_score(y_test,y_pred)
    return model, y_pred, {"Precision Score":precision,"Recall Score": recall,"F1 Score":f1,
                           "Accuracy Score":accuracy}, [fpr, tpr, roc_score],cross_entropy
```

User Defined GridSearchCV Function

In [16]:
```
def GridSearchCV_func(param_grid,model,X_train, y_train, X_test):
    # Create GridSearchCV to find the best hyperparameters
    grid_search = GridSearchCV(model, param_grid, cv=5)

    # Fit the GridSearchCV object to the training data
    grid_search.fit(X_train, y_train)

    # Get the best hyperparameters and model
    best_params = grid_search.best_params_
    best_model = grid_search.best_estimator_

    # Print the best hyperparameters
    print("Best Hyperparameters:", best_params)

    # Evaluate the best model on the test set
    accuracy = best_model.score(X_test, y_test)
    print("Accuracy on Test Set:", accuracy)
    # Prediction
    y_pred = best_model.predict(X_test)

    # Calculating precision
    precision = precision_score(y_test, y_pred)

    # Calculating recall
    recall = recall_score(y_test, y_pred)

    # Calculating F1 score
    f1 = f1_score(y_test, y_pred)

    # Calculating Accuracy score
    accuracy = accuracy_score(y_test, y_pred)

    return {"Precision Score":precision,"Recall Score": recall,"F1 Score":f1,"Accuracy Score":accuracy}
```

INFERENCE: **User defined model creation function and Gridsize function is been created for multiple use and iteration**

2. Logistic regression model

In [17]:
```
X, y = depVar, indepVar
```

In [18]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=23)
```

In [19]:
```
# LogisticRegression
clf_lr = LogisticRegression(random_state=0)
clf_lr, y_pred, score_lr, roc_auc_lr,cross_entropy_lr = model_func(clf_lr, X_train, y_train, X_test)
```

How does a unit change in each feature influence the odds of a client subscribed a term deposit or not?

In [20]:
```
coefficient_array = clf_lr.coef_
# Calculate the odds ratio
odds_ratios = np.exp(coefficient_array)
pd.DataFrame(data=odds_ratios[0],index=depVar.columns, columns=['Odds Ratio'])
```

Out[20]:

	Odds Ratio
duration	0.090569
campaign	1.044517
pdays	1.985513
previous	1.254002
emp.var.rate	4.914505
cons.price.idx	0.770812
cons.conf.idx	0.889785
euribor3m	0.418371
nr.employed	2.946871

Determining optimal threshold

In [21]:
```python
# let 'y_pred_prob' be the predicted values of y
y_pred_prob = clf_lr.predict(X_test)
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
# Finding optimal threshold using Youden's Index
youdens_table = pd.DataFrame({'TPR': tpr,
 'FPR': fpr,
'Threshold': thresholds})
# calculate the difference between TPR and FPR for each threshold and store the values in a new co
youdens_table['Difference'] = youdens_table.TPR - youdens_table.FPR
# sort the dataframe based on the values of difference
youdens_table = youdens_table.sort_values('Difference', ascending = False).reset_index(drop = True)
# print the first five observations
youdens_table.head()
```

Out[21]:

	TPR	FPR	Threshold	Difference
0	0.844246	0.148913	1	0.695333
1	0.000000	0.000000	2	0.000000
2	1.000000	1.000000	0	0.000000

For the full model, calculate the accuracy manually using the confusion matrix. Consider 0.5 as the probability threshold.

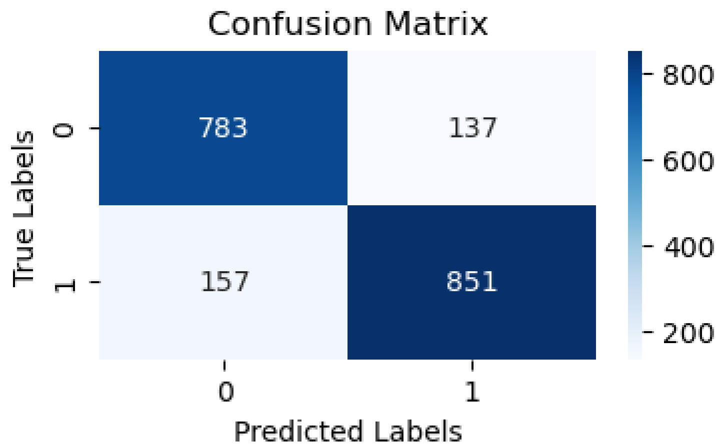
In [22]:
```
# Prediction
y_pred = clf_lr.predict(X_test)
print("Labels before applying threshold:\t",y_pred)

# Applying the probability threshold of 0.5 to obtain binary predictions
predicted_labels = (y_pred >= 0.5).astype(int)
print("Labels after applying threshold:\t",predicted_labels)

# Creating the confusion matrix
confusion_mat = confusion_matrix(y_test, predicted_labels)
# Plot the confusion matrix
plt.figure(figsize=(4,2))
sns.heatmap(confusion_mat, annot=True, cmap="Blues", fmt="d")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.show()
# Extracting the values from the confusion matrix
tn, fp, fn, tp = confusion_mat.ravel()

# Calculating accuracy manually
accuracy = (tp + tn) / (tp + tn + fp + fn)
print("Accuracy:", accuracy)
```

```
Labels before applying threshold:        [1 0 0 ... 0 1 1]
Labels after applying threshold:         [1 0 0 ... 0 1 1]
```




```
Accuracy: 0.8475103734439834
```

Calculate value of kappa for the full model . Consider threshold value as 0.18

In [23]:
```
# Prediction
y_pred = clf_lr.predict(X_test)
print("Labels before applying threshold:\t",y_pred)

# Applying the threshold of 0.18 to obtain binary predictions
predicted_labels = (y_pred >= 0.18).astype(int)
print("Labels after applying threshold:\t",predicted_labels)

# Creating the confusion matrix
confusion_mat = confusion_matrix(y_test, predicted_labels)

# Calculating kappa
kappa = cohen_kappa_score(y_test, predicted_labels)

print("Kappa:", kappa)
```

```
Labels before applying threshold:        [1 0 0 ... 0 1 1]
Labels after applying threshold:         [1 0 0 ... 0 1 1]
Kappa: 0.6946737912608808
```

Calculate the cross entropy for the logistic regression model.

In [24]:
```
# Calculating cross entropy
print("Cross Entropy:", cross_entropy_lr)
```

```
Cross Entropy: 5.2668619320288785
```

Predict whether a client subscribed a term deposit or not. For the logistic regression model find the following:

1. Precision
2. Recall
3. F_1 score

In [25]:
```
pd.DataFrame([score_lr], index=['Logistic Regression'])
```

Out[25]:

	Precision Score	Recall Score	F1 Score	Accuracy Score
Logistic Regression	0.861336	0.844246	0.852705	0.84751

3.Build a Decision Tree model and generate a classification report.

In [26]:
```
# Create a Decision Tree classifier
clf_dt = DecisionTreeClassifier()

clf_dt, y_pred , score_dt,roc_auc_dt,cross_entropy_dt = model_func(clf_dt, X_train, y_train, X_test)

# Generate a classification report
report = classification_report(y_test, y_pred)
print(report)
```

```
              precision    recall  f1-score   support

           0       0.83      0.82      0.82       920
           1       0.84      0.84      0.84      1008

    accuracy                           0.83      1928
   macro avg       0.83      0.83      0.83      1928
weighted avg       0.83      0.83      0.83      1928
```

Determining optimal hyperparameters using GridSearchCV

In [27]:
```
# Define the parameter grid to search through
param_grid = {
    'max_depth': [3, 5, 7],
    'min_samples_split': [2, 3, 4],
    'min_samples_leaf': [1, 2, 3]
}
best_model_scores_dt = GridSearchCV_func(param_grid,clf_dt,X_train, y_train, X_test)
```

```
Best Hyperparameters: {'max_depth': 5, 'min_samples_leaf': 2, 'min_samples_split': 2}
Accuracy on Test Set: 0.8713692946058091
```

Compare the Full model and optimized model using model performance metrics

In [28]:
```
pd.DataFrame([score_dt,best_model_scores_dt], index=['Full Model Score', 'Optimized Model Score'])
```

Out[28]:

	Precision Score	Recall Score	F1 Score	Accuracy Score
Full Model Score	0.835953	0.844246	0.840079	0.831950
Optimized Model Score	0.916667	0.829365	0.870833	0.871369

4.Build a Random Forest model with n_estimators=30 and generate a classification report.

In [29]:
```
# Create a Random Forest classifier
clf_rf = RandomForestClassifier(n_estimators=30)

clf_rf, y_pred, score_rf,roc_auc_rf,cross_entropy_rf= model_func(clf_rf, X_train, y_train, X_test)

# Generate a classification report
report = classification_report(y_test, y_pred)
print(report)
```

```
              precision    recall  f1-score   support

           0       0.83      0.90      0.87       920
           1       0.90      0.84      0.87      1008

    accuracy                           0.87      1928
   macro avg       0.87      0.87      0.87      1928
weighted avg       0.87      0.87      0.87      1928
```

Determining optimal hyperparameters using GridSearchCV

In [30]:
```
# Define the parameter grid to search through
param_grid = {
    'max_depth': [3, 5, 7],
    'min_samples_split': [2, 3, 4],
    'min_samples_leaf': [1, 2, 3]
}
best_model_scores_rf = GridSearchCV_func(param_grid,clf_rf,X_train, y_train, X_test)
```

```
Best Hyperparameters: {'max_depth': 7, 'min_samples_leaf': 2, 'min_samples_split': 4}
Accuracy on Test Set: 0.8744813278008299
```

Compare the Full model and optimized model using model performance metrics

In [31]:
```
pd.DataFrame([score_rf,best_model_scores_rf], index=['Full Model Score', 'Optimized Model Score'])
```

Out[31]:

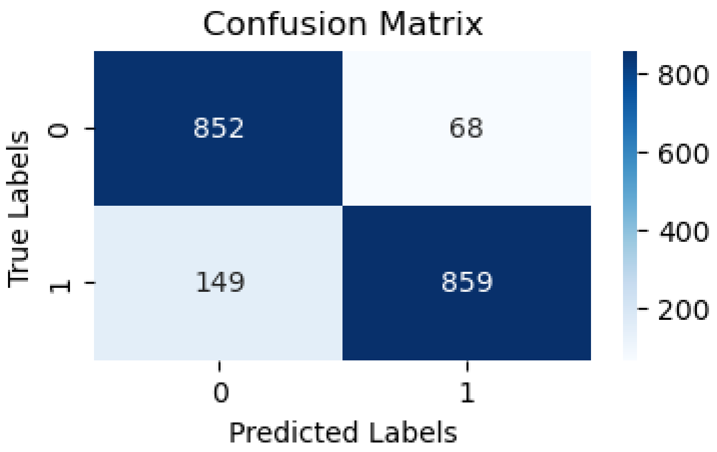
	Precision Score	Recall Score	F1 Score	Accuracy Score
Full Model Score	0.902674	0.837302	0.868760	0.867739
Optimized Model Score	0.927455	0.824405	0.872899	0.874481

5.Build the XGBoost model with a learning rate of 0.4 and gamma equal to 3. Calculate the accuracy by plotting the confusion matrix

In [32]:
```
# Create an XGBoost classifier
clf_xgb = XGBClassifier(learning_rate=0.4, gamma=3)

clf_xgb, y_pred, score_xgb,roc_auc_xgb,cross_entropy_xgb = model_func(clf_xgb, X_train, y_train, X_test)
# Generate the confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Plot the confusion matrix
plt.figure(figsize=(4,2))
sns.heatmap(cm, annot=True, cmap="Blues", fmt="d")
plt.title("Confusion Matrix")
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.show()
```



Determining optimal hyperparameters using GridSearchCV

In [33]:
```
# Define the parameter grid to search through
param_grid = {
    'learning_rate': [0.1, 0.2, 0.3],
    'gamma': [0, 1, 2, 3],
    'max_depth': [3, 5, 7]
}

best_model_scores_xgb = GridSearchCV_func(param_grid,clf_xgb,X_train, y_train, X_test)
```

```
Best Hyperparameters: {'gamma': 2, 'learning_rate': 0.2, 'max_depth': 7}
Accuracy on Test Set: 0.8874481327800829
```

Compare the Full model and optimized model using model performance metrics

In [34]:
```
pd.DataFrame([score_xgb,best_model_scores_xgb], index=['Full Model Score', 'Optimized Model Score'])
```

Out[34]:

	Precision Score	Recall Score	F1 Score	Accuracy Score
Full Model Score	0.926645	0.852183	0.887855	0.887448
Optimized Model Score	0.927568	0.851190	0.887739	0.887448

6.Build the K - Nearest Neighbor Model

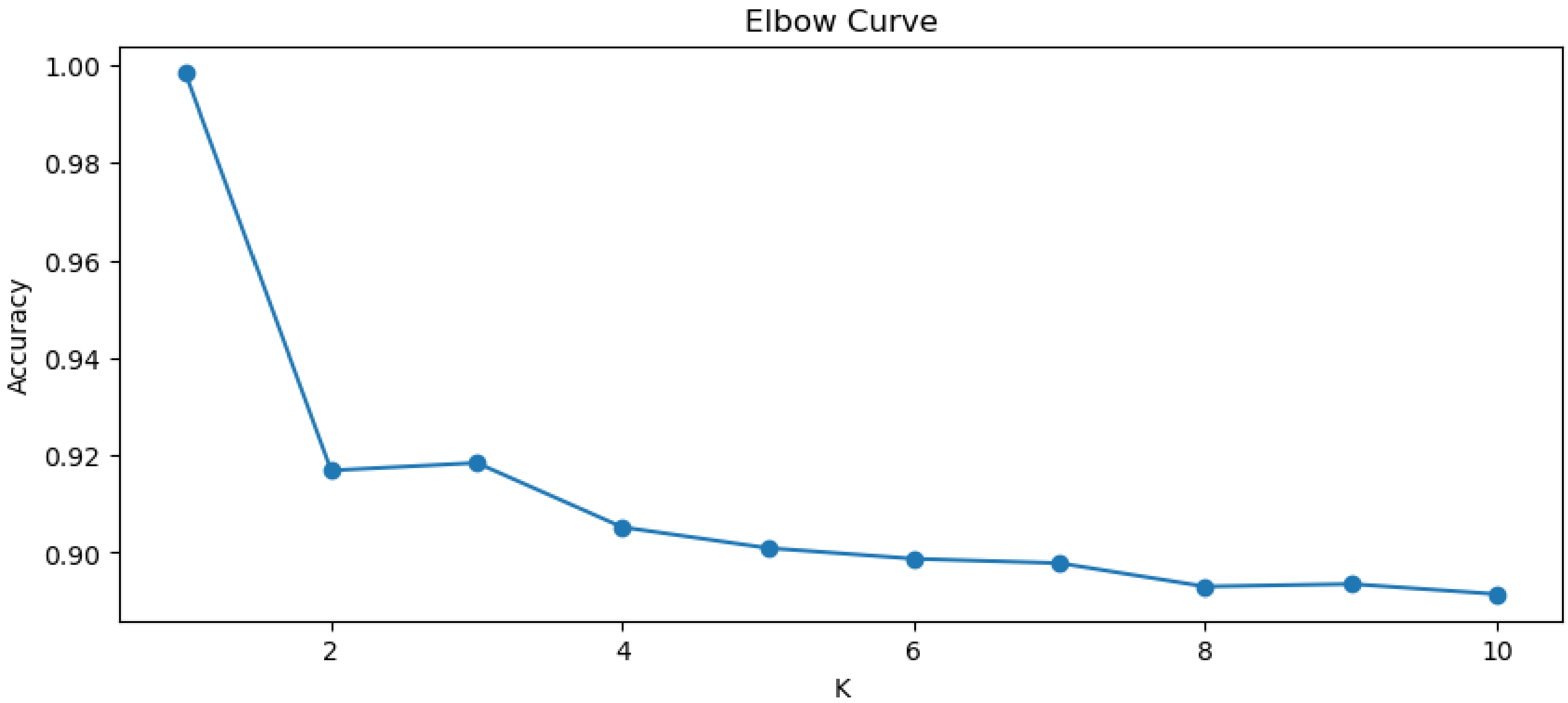
In [35]:
```
# Create a KNN classifier with k=5
clf_knn = KNeighborsClassifier(n_neighbors=5)
clf_knn, y_pred, score_knn,roc_auc_knn,cross_entropy_knn = model_func(clf_knn, X_train, y_train, X_test)
```

Determining optimal K-Value using Elbow Curve Method

In [36]:
```
k_values = range(1, 11)
inertia = []

for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    inertia.append(knn.score(X_train, y_train))

# Plot the Elbow Curve
plt.figure(figsize=(10,4))
plt.plot(k_values, inertia, marker='o')
plt.xlabel('K')
plt.ylabel('Accuracy')
plt.title('Elbow Curve')
plt.show()
```



7. Build the Naive Bayes Model

In [37]:
```
# Create a Gaussian Naive Bayes classifier
clf_g_nb = GaussianNB()
clf_g_nb, y_pred, score_g_nb,roc_auc_g_nb,cross_entropy_g_nb = model_func(clf_g_nb, X_train, y_train, X_test)
```

Compare the classification results of Gaussian, Bernoulli and Multinomial Naive Bayes

In [38]:
```
# Create Bernoulli Naive Bayes classifier
clf_b_nb = BernoulliNB()
clf_b_nb, y_pred, score_b_nb,roc_auc_b_nb,cross_entropy_b_nb = model_func(clf_b_nb, X_train, y_train, X_test)
```

In [39]:
```
X_, y_ = depVar, indepVar
```

In [40]:
```
min_scaler = MinMaxScaler()
X_ = min_scaler.fit_transform(X_)
```

In [41]:
```
X_train, X_test, y_train, y_test = train_test_split(X_, y, test_size=0.20, random_state=23)
```

In [42]:
```
# Create Multinomial Naive Bayes classifier
clf_m_nb = MultinomialNB()
clf_m_nb, y_pred, score_m_nb,roc_auc_m_nb,cross_entropy_m_nb = model_func(clf_m_nb, X_train, y_train, X_test)
```

In [43]:
```
pd.DataFrame([score_g_nb,score_b_nb,score_m_nb], index=['Gaussian Naive Bayes','Bernoulli Naive Bayes',
                                                         'Multinomial Naive Bayes'])
```

Out[43]:

	Precision Score	Recall Score	F1 Score	Accuracy Score
Gaussian Naive Bayes	0.787453	0.834325	0.810212	0.795643
Bernoulli Naive Bayes	0.732995	0.716270	0.724536	0.715249
Multinomial Naive Bayes	0.713572	0.850198	0.775917	0.743257

8. Compare the results of all above mentioned algorithms

Compare all the classification models using model performance evaluation metrics

In [44]:

```
# comaparism with respect to Accuracy score
pd.DataFrame([score_lr,score_dt,score_rf, score_xgb, score_g_nb,score_b_nb,score_m_nb],
             index=['Logistic Regression','Decision Tree','Random Forest','XGBoost',
                    'Gaussian Naive Bayes','Bernoulli Naive Bayes','Multinomial Naive Bayes']).sort_values(
    by='Accuracy Score', ascending=False)
```

Out[44]:

	Precision Score	Recall Score	F1 Score	Accuracy Score
XGBoost	0.926645	0.852183	0.887855	0.887448
Random Forest	0.902674	0.837302	0.868760	0.867739
Logistic Regression	0.861336	0.844246	0.852705	0.847510
Decision Tree	0.835953	0.844246	0.840079	0.831950
Gaussian Naive Bayes	0.787453	0.834325	0.810212	0.795643
Multinomial Naive Bayes	0.713572	0.850198	0.775917	0.743257
Bernoulli Naive Bayes	0.732995	0.716270	0.724536	0.715249

In [45]:
```
# comaparism with respect to Precession score
pd.DataFrame([score_lr,score_dt,score_rf, score_xgb, score_g_nb,score_b_nb,score_m_nb],
             index=['Logistic Regression','Decision Tree','Random Forest','XGBoost',
                    'Gaussian Naive Bayes','Bernoulli Naive Bayes','Multinomial Naive Bayes']).sort_values(
    by='Precision Score', ascending=False)
```

Out[45]:

	Precision Score	Recall Score	F1 Score	Accuracy Score
XGBoost	0.926645	0.852183	0.887855	0.887448
Random Forest	0.902674	0.837302	0.868760	0.867739
Logistic Regression	0.861336	0.844246	0.852705	0.847510
Decision Tree	0.835953	0.844246	0.840079	0.831950
Gaussian Naive Bayes	0.787453	0.834325	0.810212	0.795643
Bernoulli Naive Bayes	0.732995	0.716270	0.724536	0.715249
Multinomial Naive Bayes	0.713572	0.850198	0.775917	0.743257

In [46]:
```
# comaparism with respect to Recall score
pd.DataFrame([score_lr,score_dt,score_rf, score_xgb, score_g_nb,score_b_nb,score_m_nb],
             index=['Logistic Regression','Decision Tree','Random Forest','XGBoost',
                    'Gaussian Naive Bayes','Bernoulli Naive Bayes','Multinomial Naive Bayes']).sort_values(
    by='Recall Score', ascending=False)
```

Out[46]:

	Precision Score	Recall Score	F1 Score	Accuracy Score
XGBoost	0.926645	0.852183	0.887855	0.887448
Multinomial Naive Bayes	0.713572	0.850198	0.775917	0.743257
Logistic Regression	0.861336	0.844246	0.852705	0.847510
Decision Tree	0.835953	0.844246	0.840079	0.831950
Random Forest	0.902674	0.837302	0.868760	0.867739
Gaussian Naive Bayes	0.787453	0.834325	0.810212	0.795643
Bernoulli Naive Bayes	0.732995	0.716270	0.724536	0.715249

In [47]:
```python
# comaparism with respect to F1 score
pd.DataFrame([score_lr,score_dt,score_rf, score_xgb, score_g_nb,score_b_nb,score_m_nb],
             index=['Logistic Regression','Decision Tree','Random Forest','XGBoost',
                    'Gaussian Naive Bayes','Bernoulli Naive Bayes','Multinomial Naive Bayes']).sort_values(
    by='F1 Score', ascending=False)
```

Out[47]:

	Precision Score	Recall Score	F1 Score	Accuracy Score
XGBoost	0.926645	0.852183	0.887855	0.887448
Random Forest	0.902674	0.837302	0.868760	0.867739
Logistic Regression	0.861336	0.844246	0.852705	0.847510
Decision Tree	0.835953	0.844246	0.840079	0.831950
Gaussian Naive Bayes	0.787453	0.834325	0.810212	0.795643
Multinomial Naive Bayes	0.713572	0.850198	0.775917	0.743257
Bernoulli Naive Bayes	0.732995	0.716270	0.724536	0.715249

Compare all the classification models using their ROC curves.

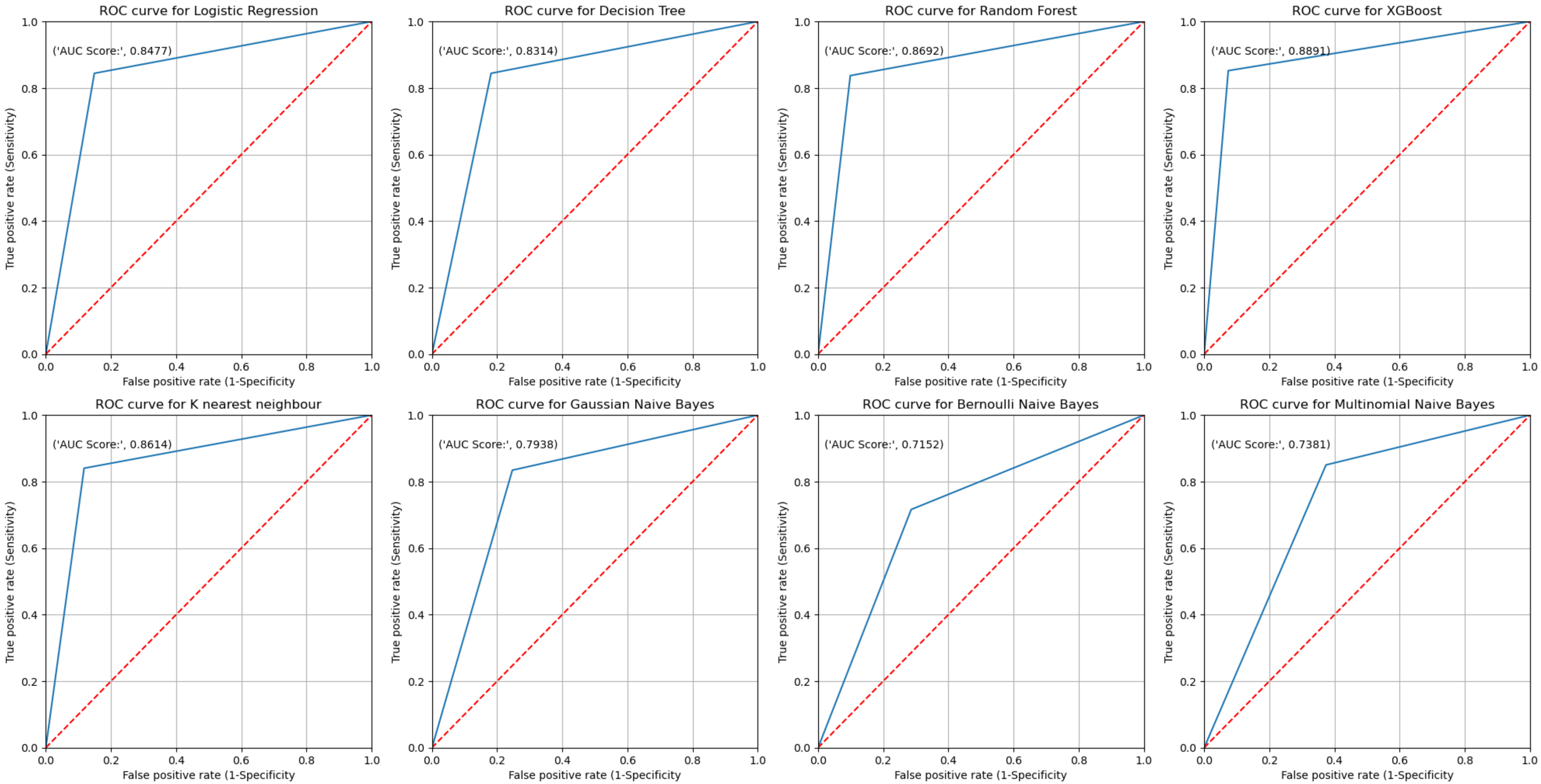
In [48]:

```
plt.figure(figsize=(20,20))
AUC_Scores = []
modelName = ['Logistic Regression',
             'Decision Tree',
             'Random Forest',
             'XGBoost',
             'K nearest neighbour',
             'Gaussian Naive Bayes','Bernoulli Naive Bayes','Multinomial Naive Bayes']
for i, roc_auc in enumerate([roc_auc_lr,roc_auc_dt,roc_auc_rf,roc_auc_xgb,
                            roc_auc_knn,roc_auc_g_nb,roc_auc_b_nb,roc_auc_m_nb]):
    plt.subplot(round(len(roc_auc))+1,4,i+1)
    plt.plot(roc_auc[0], roc_auc[1])

    # set limits for x and y axes
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.0])

    # plot the straight line showing worst prediction for the model
    plt.plot([0, 1], [0, 1],'r--')

    # add plot and axes labels
    # set text size using 'fontsize'
    plt.title('ROC curve for '+modelName[i])
    plt.xlabel('False positive rate (1-Specificity')
    plt.ylabel('True positive rate (Sensitivity)')
    plt.text(x = 0.02, y = 0.9, s = ('AUC Score:', round(roc_auc[2],4)))
    plt.grid(True)
    AUC_Scores.append( round(roc_auc[2],4))
plt.tight_layout()
```



ROC curve for Logistic Regression
('AUC Score:', 0.8477)
ROC curve for Decision Tree
('AUC Score:', 0.8314)
ROC curve for Random Forest
('AUC Score:', 0.8692)
ROC curve for XGBoost
('AUC Score:', 0.8891)
ROC curve for K nearest neighbour
('AUC Score:', 0.8614)
ROC curve for Gaussian Naive Bayes
('AUC Score:', 0.7938)
ROC curve for Bernoulli Naive Bayes
('AUC Score:', 0.7152)
ROC curve for Multinomial Naive Bayes
('AUC Score:', 0.7381)
True positive rate (Sensitivity)
False positive rate (1-Specificity
0.0
0.2
0.4
0.6
0.8
1.0

In [49]:
```
pd.DataFrame([AUC_Scores],index=['AUC_score'],columns=modelName).transpose().sort_values(
    by='AUC_score', ascending=False)
```

Out[49]:

	AUC_score
XGBoost	0.8891
Random Forest	0.8692
K nearest neighbour	0.8614
Logistic Regression	0.8477
Decision Tree	0.8314
Gaussian Naive Bayes	0.7938
Multinomial Naive Bayes	0.7381
Bernoulli Naive Bayes	0.7152

comput cross entropy and Compare all the classification models.

In [50]:
```
pd.DataFrame([cross_entropy_lr,cross_entropy_dt,cross_entropy_rf, cross_entropy_xgb, cross_entropy_g_nb,
              cross_entropy_b_nb,cross_entropy_m_nb],
             index=['Logistic Regression','Decision Tree','Random Forest','XGBoost',
                    'Gaussian Naive Bayes','Bernoulli Naive Bayes','Multinomial Naive Bayes'],
            columns=['Cross Entropy']).sort_values(by='Cross Entropy')
```

Out[50]:

	Cross Entropy
XGBoost	3.887432
Random Forest	4.568185
Logistic Regression	5.266862
Decision Tree	5.804303
Gaussian Naive Bayes	7.058330
Multinomial Naive Bayes	8.867723
Bernoulli Naive Bayes	9.835061

```
<br><br>
```

9. Intrepret your solution based on the results

1. ROC Curve: The ROC curve visualizes the trade-off between the true positive rate (TPR) and the false positive rate (FPR) for each classification model. A good classifier will have an ROC curve that is closer to the top-left corner of the plot, indicating higher TPR and lower FPR across different threshold values.

   -- As per above plots we can get that **XGBoost's** corner point is most nearer to the top-left corner'

2. AUC (Area Under the Curve): The AUC represents the overall performance of the model. A higher AUC value indicates better discrimination ability and a better-performing model. In the legend of the ROC curve plot, the AUC values are displayed for each model.

   -- As per above plots with respect to **AUC score : 0.8891** , the XGBoost fits the most

3. Model Comparison: By comparing the ROC curves and AUC values of the different models, you can assess their relative performance. A model with a higher AUC value generally indicates better predictive accuracy and a higher ability to distinguish between classes. Therefore, you can choose the model with the highest AUC value as the best-performing model for the given dataset.

   -- In total on comparing the **ROC curves and AUC score**, the XGboost helps us to get the proper classification.

4. Cross-entropy value: The **XGBoost's 3.887432** value defines that it fits for proper classification
5. With respect to classifiation metrics, the **XGBoost** algorithm stands up the top in

```
a. Accuracy Score : 0.887448
b. Precession Score : 0.926645
c. Recall Score : 0.852183
d. F1 score : 0.887855
```