Current Industry Practices and the Role of Logistic Regression in Mental Health

`Logistic regression is a widely used machine learning technique in the healthcare industry for predicting binary outcomes, such as the presence or absence of depression. It is favored for its simplicity, interpretability, and effectiveness in handling structured clinical data. In practice, logistic regression models utilize patient demographics, lifestyle factors, medical history, and psychological assessments to predict depression risk, supporting early diagnosis and personalized treatment plans in clinical settings.`

Research Landscape and Recent Developments in Depression Prediction

`Recent studies demonstrate the effectiveness of logistic regression models in accurately predicting depression by identifying significant risk factors such as age, sleep patterns, and physical activity. For instance, research by Smith et al. (2022) and Zhang et al. (2023) showed logistic regression models achieving high accuracy in depression classification. These models are praised for their ability to provide clear, interpretable results that can be easily communicated to healthcare professionals for clinical decision-making.`

Challenges, Limitations, and Future Directions

`While logistic regression is a robust tool for depression prediction, challenges such as handling multicollinearity, feature scaling, and dealing with missing data can affect model performance. Recent literature explores techniques like regularization and data imputation to overcome these limitations. The field is also moving towards integrating logistic regression with advanced machine learning methods to enhance predictive accuracy while maintaining interpretability, addressing the evolving needs of precision mental health care.`

	Variable Name	Type	Description	Values
0	Age	Numerical	The age of the individual.	Numbers
1	Marital Status	Categorical	The marital status of the individual.	Married, Single, Widowed, Divorced
2	Education Level	Categorical	The highest level of education attained by the individual.	Bachelor's Degree, High School, Associate Degree, Master's Degree, PhD
3	Number of Children	Numerical	The number of children the individual has.	0, 1, 2, 3, 4
4	Smoking Status	Categorical	Whether the individual smokes.	Non-smoker, Former, Current
5	Physical Activity Level	Categorical	The level of physical activity engaged in by the individual.	Sedentary, Moderate, Active
6	Employment Status	Categorical	The current employment status of the individual.	Employed, Unemployed
7	Income	Numerical	The annual income of the individual.	Numbers
8	Alcohol Consumption	Categorical	The level of alcohol consumption by the individual.	Moderate, Low, High
9	Dietary Habits	Categorical	The eating habits of the individual.	Unhealthy, Moderate, Healthy
10	Sleep Patterns	Categorical	The sleep patterns of the individual.	Fair, Poor, Good
11	History of Mental Illness	Categorical	Whether the individual has a history of mental illness.	No, Yes
12	History of Substance Abuse	Categorical	Whether the individual has a history of substance abuse.	No, Yes
13	Family History of Depression	Categorical	Whether there is a family history of depression.	No, Yes
14	Depression	Categorical	Whether the individual has any chronic medical conditions.	No, Yes
15	Name	Object	Name of Individual	—

Libraries

In [39]:
```python
import warnings
warnings.filterwarnings("ignore")

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression, RidgeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, precision_recall_fscore_support, accuracy_score, confusion_matrix, roc_curve, roc_auc_score
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import OneHotEncoder
from sklearn.ensemble import VotingClassifier
from matplotlib.colors import ListedColormap

import time
```

In [40]:
```python
import pyarrow as pa
import pyarrow.parquet as pq

file = pd.read_csv("depression_data.csv")
table = pa.Table.from_pandas(file)
pq.write_table(table, "depression_data.parquet")
```

Tell Time - Decorator for calculating the time

In [41]:
```python
def tell_time(function, *args, **kwargs):
    def wrapper(*args, **kwargs):
        start = time.time()
        done = function(*args, **kwargs)
        print(f"{function.__name__}() function took - {(time.time()-start)//60} Mins {(time.time()-start)%60:.3f} Sec")
        return done
    return wrapper
```

In [42]:
```python
@tell_time
def read_csv_data(file):
    return pd.read_csv(file)
```

In [43]:
```python
@tell_time
def read_parquet_data(file):
    return pd.read_parquet(file)
```

Reading the Dataset

In [44]:
```
csv_df = read_csv_data("depression_data.csv")
```
```
read_csv_data() function took - 0.0 Mins 0.426 Sec
```

In [45]:
```
parquet_df = read_parquet_data("depression_data.parquet")
```
```
read_parquet_data() function took - 0.0 Mins 0.226 Sec
```

In [46]:
```
df = parquet_df
```

In [47]:
```
df.rename(columns={"Chronic Medical Conditions":"Depression"}, inplace=True)
```

In [48]:
```
df.head(3)
```

Out[48]:

	Name	Age	Marital Status	Education Level	Number of Children	Smoking Status	Physical Activity Level	Employment Status	Income	Alcohol Consumption	Dietary Habits	Sleep Patterns	History of Mental Illness	History of Substance Abuse	Family History of Depression	Depression
0	Christine Barker	31	Married	Bachelor's Degree	2	Non-smoker	Active	Unemployed	26265.67	Moderate	Moderate	Fair	Yes	No	Yes	Yes
1	Jacqueline Lewis	55	Married	High School	1	Non-smoker	Sedentary	Employed	42710.36	High	Unhealthy	Fair	Yes	No	No	Yes
2	Shannon Church	78	Widowed	Master's Degree	1	Non-smoker	Sedentary	Employed	125332.79	Low	Unhealthy	Good	No	No	Yes	No

---

Inspection of Dataset

In [49]:
```
df.shape
```

Out[49]:
```
(413768, 16)
```

In [50]:
```
df.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 413768 entries, 0 to 413767
Data columns (total 16 columns):
 #   Column                        Non-Null Count   Dtype  
---  ------                        --------------   -----  
 0   Name                          413768 non-null  object 
 1   Age                           413768 non-null  int64  
 2   Marital Status                413768 non-null  object 
 3   Education Level               413768 non-null  object 
 4   Number of Children            413768 non-null  int64  
 5   Smoking Status                413768 non-null  object 
 6   Physical Activity Level       413768 non-null  object 
 7   Employment Status             413768 non-null  object 
 8   Income                        413768 non-null  float64
 9   Alcohol Consumption           413768 non-null  object 
 10  Dietary Habits                413768 non-null  object 
 11  Sleep Patterns                413768 non-null  object 
 12  History of Mental Illness     413768 non-null  object 
 13  History of Substance Abuse    413768 non-null  object 
 14  Family History of Depression  413768 non-null  object 
 15  Depression                    413768 non-null  object 
dtypes: float64(1), int64(2), object(13)
memory usage: 50.5+ MB
```

In [51]:
```
df["Number of Children"].value_counts()
```

Out[51]:
```
Number of Children
0    155232
2     83961
1     83925
3     76974
4     13676
Name: count, dtype: int64
```

In [52]:
```
df["Number of Children"] = df["Number of Children"].astype("object")
```

Statistical Inferences - 5 Point Summary & describe

In [53]:
```
df.describe(include="number")
```

Out[53]:

	Age	Income
count	413768.000000	413768.000000
mean	49.000713	50661.707971
std	18.158759	40624.100565
min	18.000000	0.410000
25%	33.000000	21001.030000
50%	49.000000	37520.135000
75%	65.000000	76616.300000
max	80.000000	209995.220000

In [54]:
```
df.describe(exclude="number")
```

Out[54]:

	Name	Marital Status	Education Level	Number of Children	Smoking Status	Physical Activity Level	Employment Status	Alcohol Consumption	Dietary Habits	Sleep Patterns	History of Mental Illness	History of Substance Abuse	Family History of Depression	Depression
count	413768	413768	413768	413768	413768	413768	413768	413768	413768	413768	413768	413768	413768	413768
unique	196851	4	5	5	3	3	2	3	3	3	2	2	2	2
top	Michael Smith	Married	Bachelor's Degree	0	Non-smoker	Sedentary	Employed	Moderate	Unhealthy	Fair	No	No	No	No
freq	198	240444	124329	155232	247416	176850	265659	173440	170817	196789	287943	284880	302515	277561

Cleaning the Data - Nulls & Duplicates

In [55]:
```
df.duplicated().sum()
```

Out[55]:
```
np.int64(0)
```

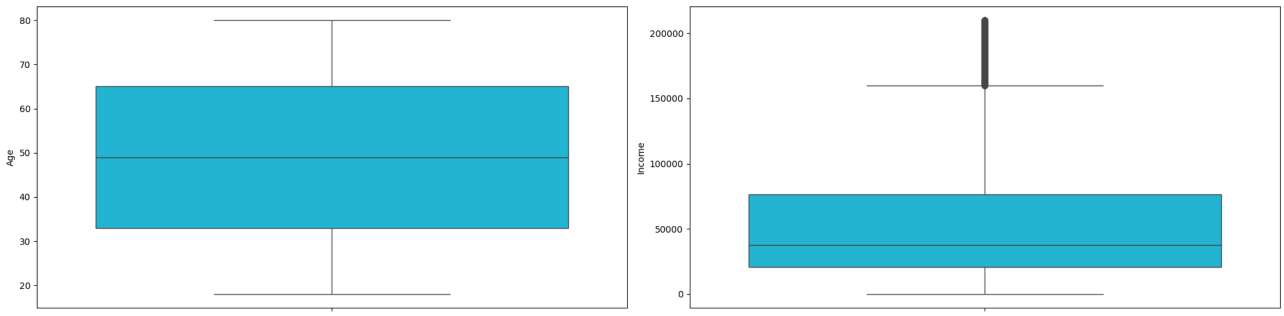
In [56]:
```
df.isnull().sum()
```

Out[56]:
```
Name                            0
Age                             0
Marital Status                  0
Education Level                 0
Number of Children              0
Smoking Status                  0
Physical Activity Level         0
Employment Status               0
Income                          0
Alcohol Consumption             0
Dietary Habits                  0
Sleep Patterns                  0
History of Mental Illness       0
History of Substance Abuse      0
Family History of Depression    0
Depression                      0
dtype: int64
```

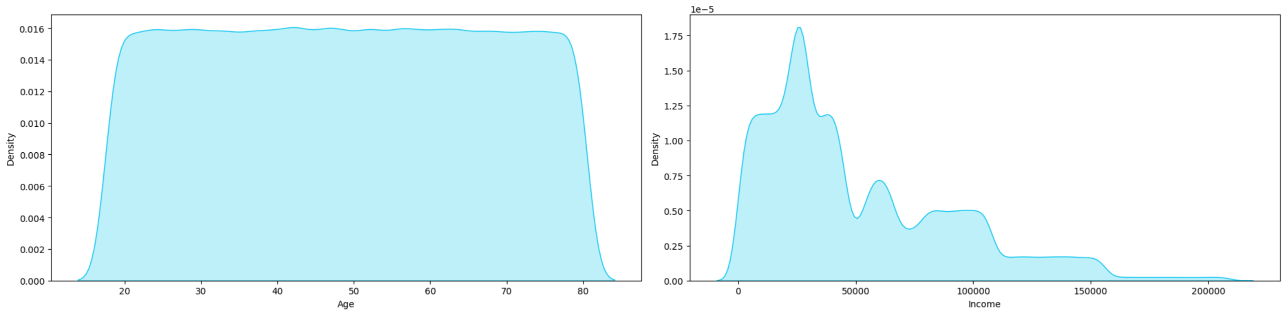
In [57]:
```
df.drop("Name", axis=1, inplace=True)
```

Plots

In [58]:
```
fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(20,5))

for feature, ax_object in zip(df.select_dtypes(include="number").columns, ax.flatten()):
    sns.boxplot(df[feature], ax=ax_object, color="#05C7F2")


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



In [59]:
```
fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(20,5))

for feature, ax_object in zip(df.select_dtypes(include="number").columns, ax.flatten()):
    sns.kdeplot(df[feature], ax=ax_object, fill=True, color="#05C7F2")


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



In [60]:
```
fig, axes = plt.subplots(nrows=4, ncols=4, figsize=(20, 7))

for i in range(13):

    feature = ['Marital Status', 'Education Level', 'Number of Children',
       'Smoking Status', 'Physical Activity Level', 'Employment Status',
       'Alcohol Consumption', 'Dietary Habits', 'Sleep Patterns',
       'History of Mental Illness', 'History of Substance Abuse',
       'Family History of Depression', 'Depression']
```

```python
    category = df[feature[i]].value_counts().index
    percentage = [f"{i:.2f}%" for i in (df[feature[i]].value_counts().values/df.shape[0])*100]

    f_table = pd.DataFrame({"Category":category, "Percentage":percentage})

    axes[i//4, i%4].axis('tight')
    axes[i//4, i%4].axis('off')
    axes[i//4, i%4].table(cellText=f_table.values, colLabels=f_table.columns, loc="center", cellLoc="center", fontsize=15, colColours=["#05C7F2"]*13)
    axes[i//4, i%4].set_title(feature[i])



axes[3, 1].axis('off')
axes[3, 2].axis('off')
axes[3, 3].axis('off')

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

Marital Status

Category	Percentage
Married	58.11%
Single	17.43%
Widowed	16.55%
Divorced	7.91%

Education Level

Category	Percentage
Bachelor's Degree	30.05%
High School	28.74%
Associate Degree	19.33%
Master's Degree	17.83%
PhD	4.05%

Number of Children

Category	Percentage
0	37.52%
2	20.29%
1	20.28%
3	18.60%
4	3.31%

Smoking Status

Category	Percentage
Non-smoker	59.80%
Former	28.08%
Current	12.12%

Physical Activity Level

Category	Percentage
Sedentary	42.74%
Moderate	38.19%
Active	19.07%

Employment Status

Category	Percentage
Employed	64.20%
Unemployed	35.80%

Alcohol Consumption

Category	Percentage
Moderate	41.92%
Low	33.65%
High	24.43%

Dietary Habits

Category	Percentage
Unhealthy	41.28%
Moderate	41.19%
Healthy	17.52%

Sleep Patterns

Category	Percentage
Fair	47.56%
Poor	31.32%
Good	21.12%

History of Mental Illness

Category	Percentage
No	69.59%
Yes	30.41%

History of Substance Abuse

Category	Percentage
No	68.85%
Yes	31.15%

Family History of Depression

Category	Percentage
No	73.11%
Yes	26.89%

Depression

Category	Percentage
No	67.08%
Yes	32.92%

Hypothesis Testing

In [61]:
```python
from scipy.stats import chi2_contingency, mannwhitneyu, chi2
```

`H0 : There is no relationship among two variables`

`H1 : There is relationship among two variables`

In [62]:
```python
hypo_test = {}
nums = ["Age", "Income"]

for i in parquet_df.columns:
    if i in nums:
        mini_df = parquet_df[["Depression", i]]
        cat_one = mini_df[mini_df["Depression"] == "No"][i]
        cat_two = mini_df[mini_df["Depression"] == "Yes"][i]
        test = mannwhitneyu(cat_one, cat_two)
        hypo_test[i] = {"Statistic":test[0], "P-Value":test[1]}
    else:
        test = chi2_contingency(pd.crosstab(parquet_df["Depression"], parquet_df[i]))
        hypo_test[i] = {"Statistic":test[0], "P-Value":test[1]}

hypo_test.pop("Depression")

statistic = [i["Statistic"] for i in hypo_test.values()]
p_Value = [i["P-Value"] for i in hypo_test.values()]
```

In [63]:
```python
a = pd.DataFrame(data={
    "Target Variable":["Depression (2 Categories)"]*14,
    "Another Variable":['Age (Numerical)', 'Marital Status (4 Categories)', 'Education Level (5 Categories)', 'Number of Children (5 Categories)',
      'Smoking Status (3 Categories)', 'Physical Activity Level (3 Categories)', 'Employment Status (2 Categories)',
      'Income (Numerical)', 'Alcohol Consumption (3 Categories)', 'Dietary Habits (3 Categories)', 'Sleep Patterns (3 Categories)',
      'History of Mental Illness (2 Categories)', 'History of Substance Abuse (2 Categories)',
      'Family History of Depression (2 Categories)'],
    "Type of Hypothisis Test":['Mann-Whitney U Test', 'Chi-Square Test', 'Chi-Square Test', 'Chi-Square Test', 'Chi-Square Test', 'Chi-Square Test',
                               'Chi-Square Test','Mann-Whitney U Test', 'Chi-Square Test', 'Chi-Square Test', 'Chi-Square Test', 'Chi-Square Test', 'Chi-Square Test', 'Chi-
Square Test'],
    "Statistic":statistic,
    "P-Value":p_Value,
    "Relationship":["There is a relationship" if i<0.05 else "No relationship" for i in p_Value]


})
# a
# print(a.to_markdown())
```

	Target Variable	Another Variable	Type of Hypothisis Test	Statistic	P-Value	Relationship
0	Depression (2 Categories)	Age (Numerical)	Mann-Whitney U Test	1.93121e+10	8.65343e-30	There is a relationship
1	Depression (2 Categories)	Marital Status (4 Categories)	Chi-Square Test	66.9861	1.88552e-14	There is a relationship
2	Depression (2 Categories)	Education Level (5 Categories)	Chi-Square Test	4.92712	0.294857	No relationship
3	Depression (2 Categories)	Number of Children (5 Categories)	Chi-Square Test	37.4444	1.45881e-07	There is a relationship
4	Depression (2 Categories)	Smoking Status (3 Categories)	Chi-Square Test	1166.17	5.8947e-254	There is a relationship
5	Depression (2 Categories)	Physical Activity Level (3 Categories)	Chi-Square Test	527.441	2.93487e-115	There is a relationship
6	Depression (2 Categories)	Employment Status (2 Categories)	Chi-Square Test	744.135	7.56388e-164	There is a relationship
7	Depression (2 Categories)	Income (Numerical)	Mann-Whitney U Test	1.97126e+10	2.13549e-111	There is a relationship
8	Depression (2 Categories)	Alcohol Consumption (3 Categories)	Chi-Square Test	106.272	8.38038e-24	There is a relationship

	Target Variable	Another Variable	Type of Hypothisis Test	Statistic	P-Value	Relationship
9	Depression (2 Categories)	Dietary Habits (3 Categories)	Chi-Square Test	114.2	1.59109e-25	There is a relationship
10	Depression (2 Categories)	Sleep Patterns (3 Categories)	Chi-Square Test	123.653	1.40935e-27	There is a relationship
11	Depression (2 Categories)	History of Mental Illness (2 Categories)	Chi-Square Test	15.0563	0.000104351	There is a relationship
12	Depression (2 Categories)	History of Substance Abuse (2 Categories)	Chi-Square Test	4.50934	0.0337103	There is a relationship
13	Depression (2 Categories)	Family History of Depression (2 Categories)	Chi-Square Test	2.12851	0.144581	No relationship

In [64]:
```
df = parquet_df.copy()
df.drop(columns=["Education Level", "Family History of Depression"], inplace=True)
```

In [ ]:

In [65]:
```
df.head()
```

Out[65]:

	Age	Marital Status	Number of Children	Smoking Status	Physical Activity Level	Employment Status	Income	Alcohol Consumption	Dietary Habits	Sleep Patterns	History of Mental Illness	History of Substance Abuse	Depression
0	31	Married	2	Non-smoker	Active	Unemployed	26265.67	Moderate	Moderate	Fair	Yes	No	Yes
1	55	Married	1	Non-smoker	Sedentary	Employed	42710.36	High	Unhealthy	Fair	Yes	No	Yes
2	78	Widowed	1	Non-smoker	Sedentary	Employed	125332.79	Low	Unhealthy	Good	No	No	No
3	58	Divorced	3	Non-smoker	Moderate	Unemployed	9992.78	Moderate	Moderate	Poor	No	No	No
4	18	Single	0	Non-smoker	Sedentary	Unemployed	8595.08	Low	Moderate	Fair	Yes	No	Yes

Spliting the data

In [66]:
```
le_object = LabelEncoder()
df["Depression"] = le_object.fit_transform(df["Depression"])
raw_df = df
target = df["Depression"]
df = df.drop(columns="Depression")
```

In [67]:
```
x_train, x_test, y_train, y_test = train_test_split(df, target, test_size=0.05, random_state=5)
```

In [68]:
```
print(f'''
x_train shape : {x_train.shape}
x_test shape : {x_test.shape}
y_train shape : {y_train.shape}
y_test shape : {y_test.shape}
''')
```

```
x_train shape : (393079, 12)
x_test shape : (20689, 12)
y_train shape : (393079,)
y_test shape : (20689,)
```

Transformation

Scaling

In [69]:
```
x_train.select_dtypes(include="number").head(5)
```

Out[69]:

	Age	Income
13513	49	104852.57
324041	59	24365.22
144337	78	29327.34
250003	43	27478.55
47584	75	9891.63

In [70]:
```
scaler_objects = {}
def do_scaling(x_train, x_test, scaler_object=MinMaxScaler()):


    for i in x_train.select_dtypes(include="number").columns:
        scaler_objects[i] = MinMaxScaler()
        scaler_objects[i].fit(x_train[[i]])
        x_train[i] = scaler_objects[i].transform(x_train[[i]])

    for i in x_test.select_dtypes(include="number").columns:
        x_test[i] = scaler_objects[i].transform(x_test[[i]])

    return x_train, x_test
```

In [71]:
```
x_train, x_test = do_scaling(x_train=x_train, x_test=x_test)
```

In [72]:
```
x_train.head()
```

Out[72]:

	Age	Marital Status	Number of Children	Smoking Status	Physical Activity Level	Employment Status	Income	Alcohol Consumption	Dietary Habits	Sleep Patterns	History of Mental Illness	History of Substance Abuse
13513	0.500000	Married	1	Current	Moderate	Employed	0.499308	High	Unhealthy	Poor	No	No
324041	0.661290	Married	1	Non-smoker	Sedentary	Employed	0.116026	Moderate	Moderate	Fair	Yes	Yes
144337	0.967742	Married	3	Non-smoker	Moderate	Employed	0.139655	Moderate	Moderate	Fair	No	Yes
250003	0.403226	Married	1	Former	Sedentary	Unemployed	0.130852	High	Moderate	Poor	Yes	No
47584	0.919355	Widowed	2	Former	Moderate	Unemployed	0.047102	High	Unhealthy	Poor	Yes	No

In [73]:
```python
x_test.head()
```

Out[73]:

	Age	Marital Status	Number of Children	Smoking Status	Physical Activity Level	Employment Status	Income	Alcohol Consumption	Dietary Habits	Sleep Patterns	History of Mental Illness	History of Substance Abuse
366559	0.080645	Married	2	Non-smoker	Active	Unemployed	0.138907	Moderate	Healthy	Fair	No	No
66432	0.129032	Single	0	Current	Sedentary	Employed	0.354114	High	Unhealthy	Fair	Yes	Yes
243274	0.935484	Married	2	Non-smoker	Moderate	Employed	0.613201	High	Healthy	Poor	No	No
209153	0.096774	Married	1	Non-smoker	Active	Employed	0.410786	Low	Healthy	Poor	No	No
394294	0.919355	Married	1	Non-smoker	Moderate	Employed	0.416343	Moderate	Healthy	Fair	No	No

In [74]:
```python
# scaler_objects = {}

# for i in x_train.select_dtypes(include="number").columns:
#     scaler_objects[i] = MinMaxScaler()
#     scaler_objects[i].fit(x_train[[i]])
#     x_train[i] = scaler_objects[i].transform(x_train[[i]])
```

In [75]:
```python
x_train.select_dtypes(include="number").head(5)
```

Out[75]:

	Age	Income
13513	0.500000	0.499308
324041	0.661290	0.116026
144337	0.967742	0.139655
250003	0.403226	0.130852
47584	0.919355	0.047102

In [76]:
```python
for i in x_test.select_dtypes(include="number").columns:
    x_test[i] = scaler_objects[i].transform(x_test[[i]])
```

Encoding

In [77]:
```python
new_df = x_train.select_dtypes(include="number")
new_df.reset_index(inplace=True)
encoder_objects = {}

for i in x_train.select_dtypes(exclude="number").columns:
    # print(i)
    encoder_objects[i] = OneHotEncoder(dtype='int', drop="first")
    dummy_df = encoder_objects[i].fit_transform(x_train[[i]]).toarray()
    new_df = pd.concat([new_df, pd.DataFrame(dummy_df, columns=encoder_objects[i].get_feature_names_out())], axis=1)
    # print(new_df)

x_train = new_df
```

In [78]:
```python
new_df = x_test.select_dtypes(include="number")
new_df.reset_index(inplace=True)

for i in x_test.select_dtypes(exclude="number").columns:
    dummy_df = encoder_objects[i].transform(x_test[[i]]).toarray()
    new_df = pd.concat([new_df, pd.DataFrame(dummy_df, columns=encoder_objects[i].get_feature_names_out())], axis=1)
    # print(new_df)

x_test = new_df
```

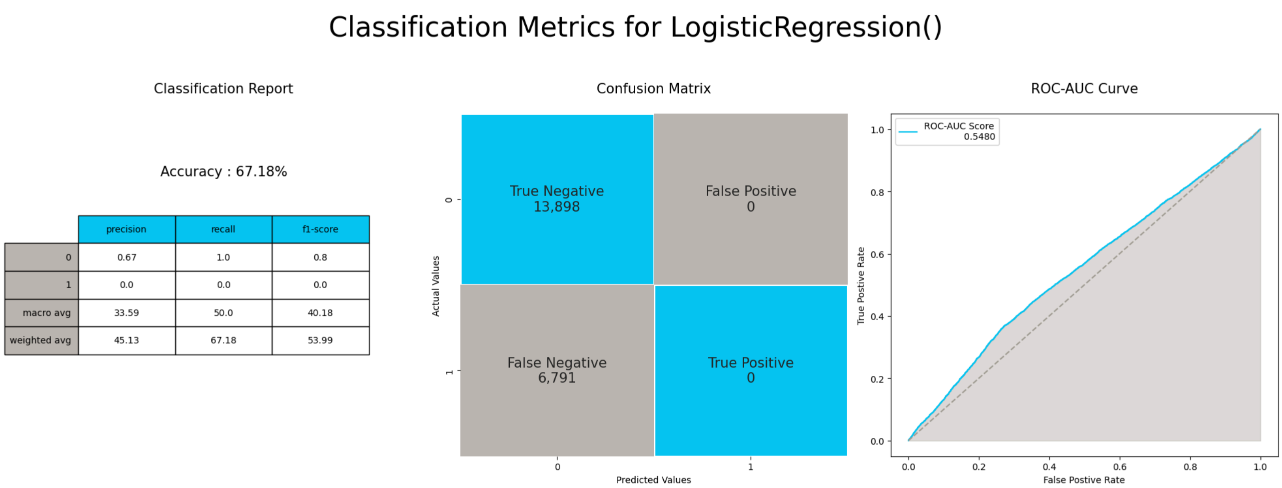
In [79]:
```python
x_train.drop(columns="index", inplace=True)
x_test.drop(columns="index", inplace=True)
```

Base Model - Logistic Regression

In [80]:
```python
def get_metrics(model, x_test, y_test):
    '''
    Parameters:
    -----------------------
    model : ML Model Object i.e., LiniearRegression()

    x_test : Featuers Testing DataFrame from train_test_split()

    y_test : Target Testing DataFrame from train_test_split()

    _______________________
    Returns:
    -----------------------
    subplots(3) : Clasification Report, Confusion Matrix, ROC-AUC Curve



    ____________________________________________________________

    '''
    y_pred = model.predict(x_test)
    fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(20, 8))

    model_name = model if len(str(model)) <= 50 else str(model)[:50]+"...)"
    fig.suptitle(f"\nClassification Metrics for {model_name}\n", fontsize=30)

    ###########################################################################################################
    cr = pd.DataFrame(classification_report(y_test, y_pred, output_dict=True)).T.iloc[:, :3]
    accuracy = round((float(cr.loc["accuracy"][0]))*100, 2)
    t = cr.iloc[[0,1,3,4], :]
    t.loc[["macro avg", "weighted avg"]] = t.loc[["macro avg", "weighted avg"]]*100
    t = round(t, 2)

    axes[0].axis('tight')
    axes[0].axis('off')
    t = axes[0].table(cellText=t.values, colLabels=t.columns, rowLabels=t.index, loc="center", cellLoc="center", rowLoc='right', fontsize=5, colColours=['#05C7F2']*3,
rowColours=["#BCB7B1"]*4, colWidths=[0.25]*3)
    t.scale(1, 3)
    axes[0].set_title(f"Classification Report\n", fontsize=15)
    axes[0].text(x=-0.018, y=0.035, s=f"Accuracy : {accuracy}%", fontsize=15)
```

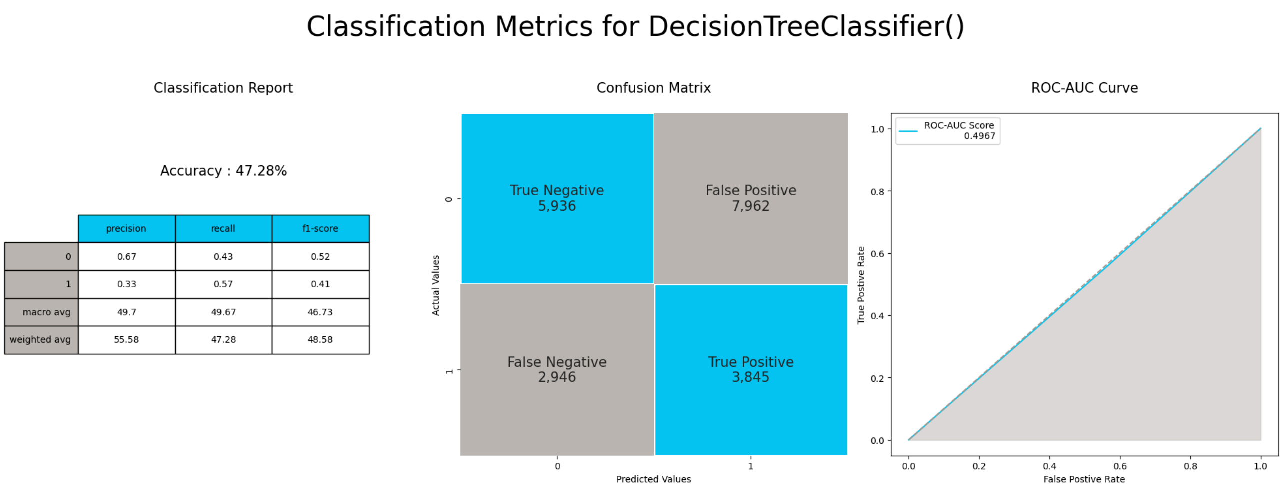
```
    ##############################################################################################
    ##############################################################################################
    ##############################################################################################
    ##############################################################################################
    l = np.array(["True Negative", "False Positive", "False Negative", "True Positive"])
    cm = confusion_matrix(y_test, y_pred)
    c = cm.flatten()
    sns.heatmap(confusion_matrix(y_test, y_pred), annot=np.array([f"{i}\n{j:,}" for i, j in zip(l, c)]).reshape(2,2), fmt="", cbar=False, ax=axes[1], cmap =
ListedColormap(['#05C7F2']), linewidths = 1, annot_kws = {'size':15})
    for i in range(cm.shape[0]):
        for j in range(cm.shape[1]):
            if i != j:  # Check if not diagonal
                # Set cell background to white
                rect = plt.Rectangle((j, i), 1, 1, facecolor='#BCB7B1')
                axes[1].add_patch(rect)
    axes[1].set_xlabel("Predicted Values")
    axes[1].set_ylabel("Actual Values")
    axes[1].axis('tight')
    axes[1].set_title(f"Confusion Matrix\n", fontsize=15)
    ##############################################################################################
    ##############################################################################################
    ##############################################################################################
    ##############################################################################################
    fpr, tpr, _ = roc_curve(y_test, model.predict_proba(x_test)[:,1])
    axes[2].plot(fpr, tpr, color='#05C7F2', label=f"ROC-AUC Score\n              {roc_auc_score(y_test, model.predict_proba(x_test)[:,1]):.4f}", fillstyle="full")
    axes[2].plot([0, 1], [0, 1],color='#A19C95', linestyle='dashed')
    axes[2].fill_between(fpr, tpr, alpha=0.5, color='#BCB7B1')
    axes[2].set_xlabel("False Postive Rate")
    axes[2].set_ylabel("True Postive Rate")
    axes[2].legend(loc="upper left")
    axes[2].set_title(f"ROC-AUC Curve\n", fontsize=15)
    ##############################################################################################

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

In [81]:
```
model = LogisticRegression().fit(x_train, y_train)
get_metrics(model, x_test, y_test)
```



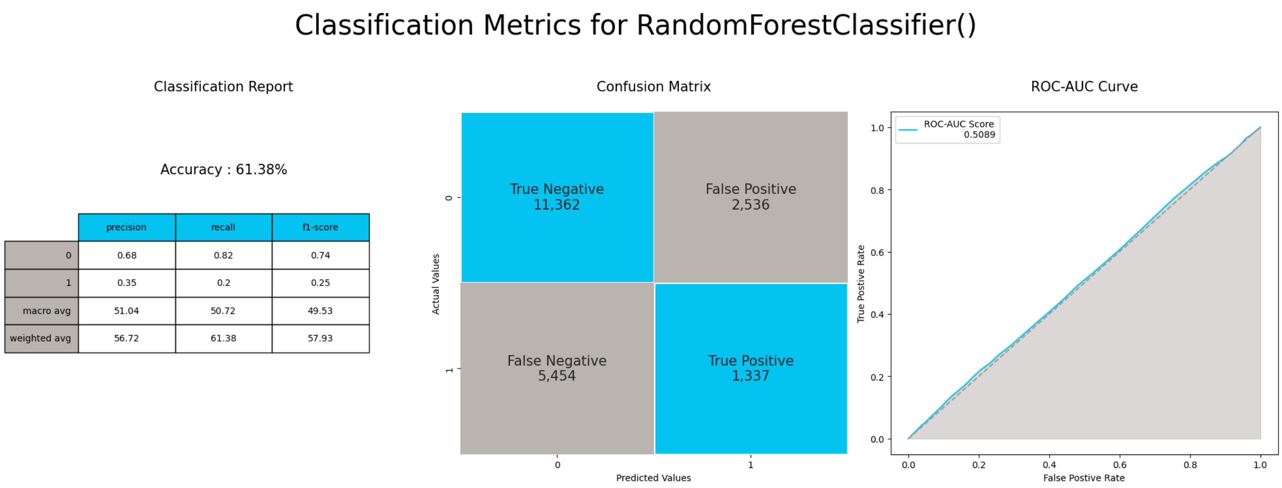
In [82]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [83]:
```
model = DecisionTreeClassifier().fit(x_train, y_train)
get_metrics(model, x_test, y_test)
```



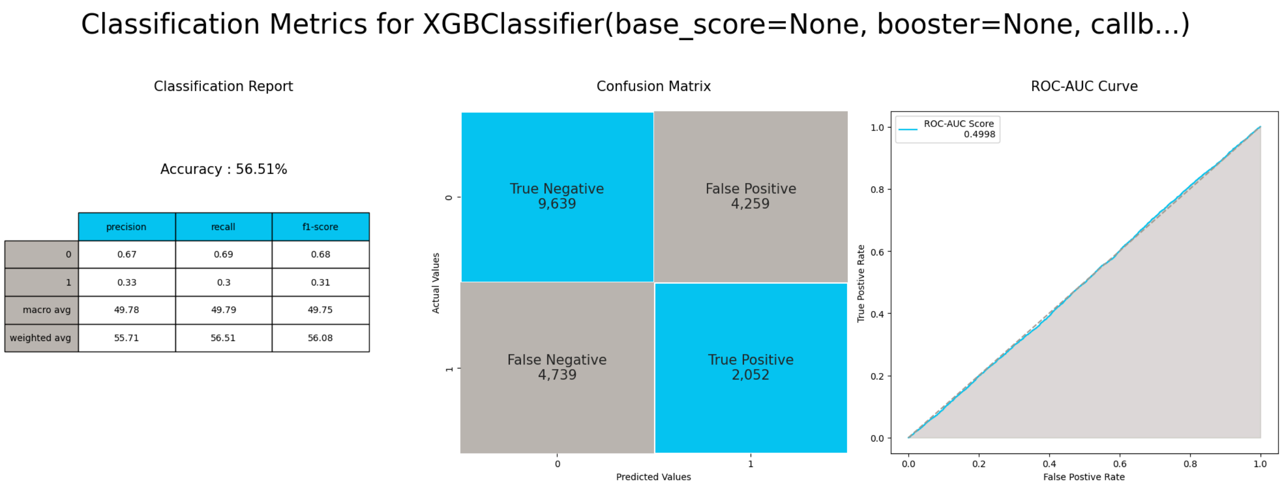
In [84]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [85]:
```
model = RandomForestClassifier().fit(x_train, y_train)
get_metrics(model, x_test, y_test)
```

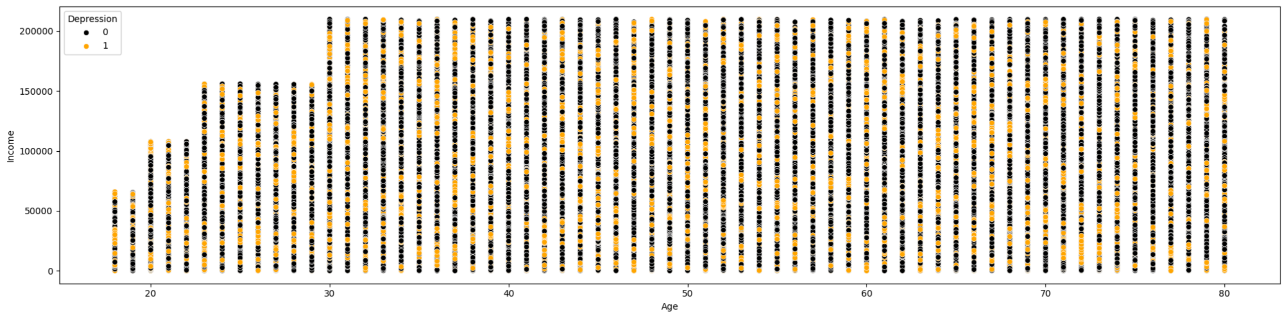


In [86]:
```python
from xgboost.sklearn import XGBClassifier
```

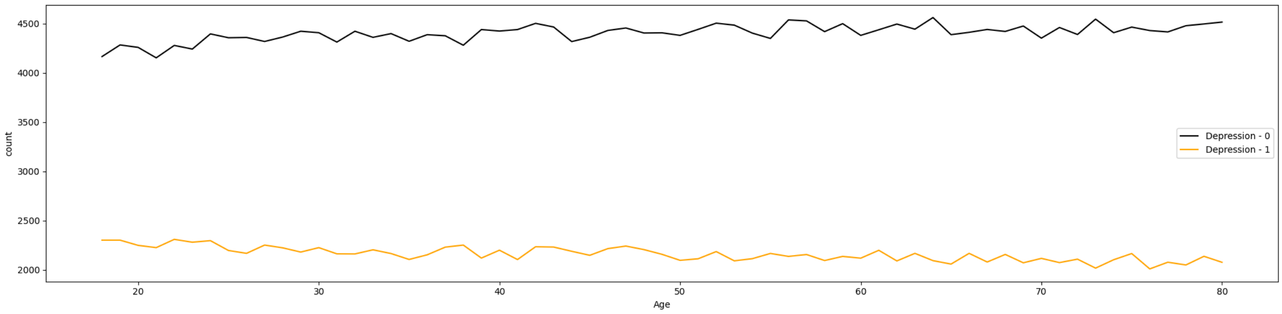
In [87]:
```python
model = XGBClassifier().fit(x_train, y_train)
get_metrics(model, x_test, y_test)
```



In [88]:
```python
plt.figure(figsize=(20,5))

sns.scatterplot(x=raw_df['Age'], y=raw_df['Income'], hue=raw_df["Depression"], palette=["Black", "Orange"])

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



In [89]:
```python
plt.figure(figsize=(20,5))

sns.lineplot(raw_df[raw_df["Depression"] == 0]["Age"].value_counts(), color="BLack", errorbar=None, label="Depression - 0")
sns.lineplot(raw_df[raw_df["Depression"] == 1]["Age"].value_counts(), color="Orange", errorbar=None, label="Depression - 1")

plt.legend(loc="center right")
plt.tight_layout()
plt.show()
```



In [90]:
```
dummy_df = parquet_df.select_dtypes(include="number")
```

In [91]:
```
for i in parquet_df.select_dtypes(exclude="number").columns:
    dummy_df[i] = LabelEncoder().fit_transform(parquet_df[i])
```

In [92]:
```
# a = OneHotEncoder(drop="first").fit(parquet_df.select_dtypes(exclude="number"))
# b = a.transform(parquet_df.select_dtypes(exclude="number")).toarray()
# for i in range(len(a.get_feature_names_out())):
#     dummy_df[a.get_feature_names_out()[i]] = b[:, i]
```

In [ ]:
```

```

In [93]:
```
dummy_df
```

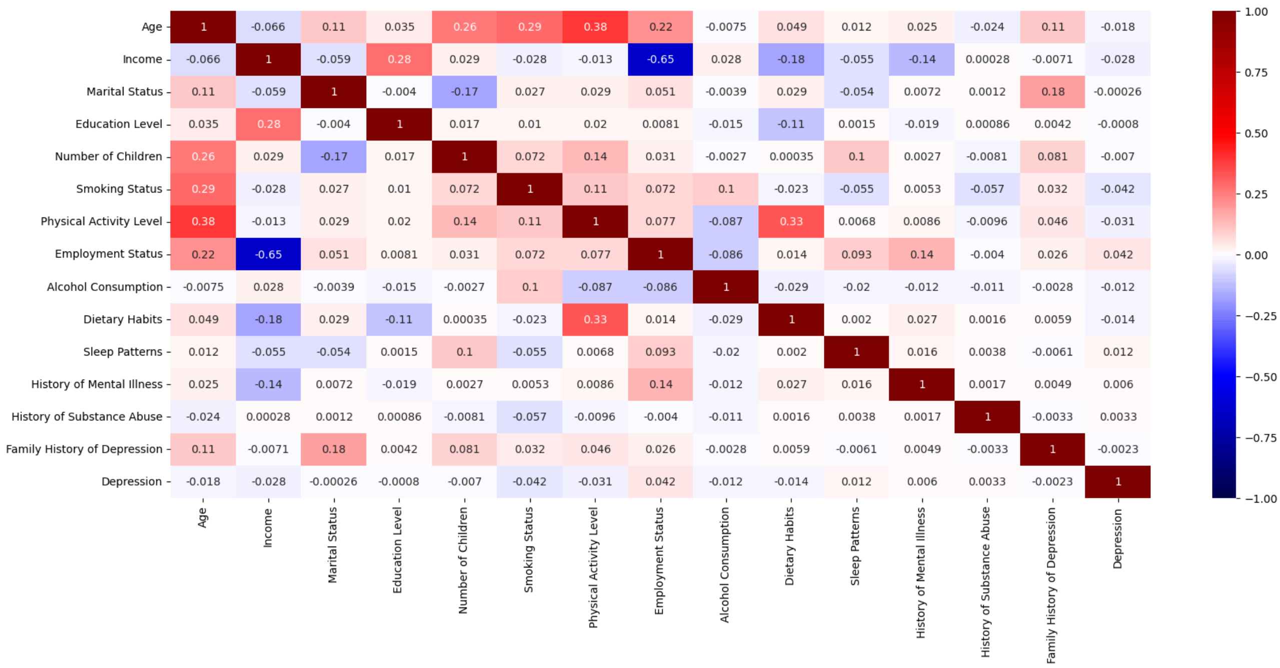
Out[93]:

	Age	Income	Marital Status	Education Level	Number of Children	Smoking Status	Physical Activity Level	Employment Status	Alcohol Consumption	Dietary Habits	Sleep Patterns	History of Mental Illness	History of Substance Abuse	Family History of Depression	Depression
0	31	26265.67	1	1	2	2	0	1	2	1	0	1	0	1	1
1	55	42710.36	1	2	1	2	2	0	0	2	0	1	0	0	1
2	78	125332.79	3	3	1	2	2	0	1	2	1	0	0	1	0
3	58	9992.78	0	3	3	2	1	1	2	1	2	0	0	0	0
4	18	8595.08	2	2	0	2	2	1	1	1	0	1	0	1	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
413763	68	109233.43	1	3	0	1	1	0	1	0	1	0	0	0	0
413764	26	96760.97	2	1	0	0	0	0	1	0	2	1	1	0	1
413765	57	77353.26	1	1	0	2	2	0	2	1	0	0	0	1	1
413766	71	24557.08	1	0	2	2	2	1	2	1	2	0	1	0	0
413767	62	107125.74	3	3	0	1	1	0	2	0	1	0	1	0	0

413768 rows × 15 columns

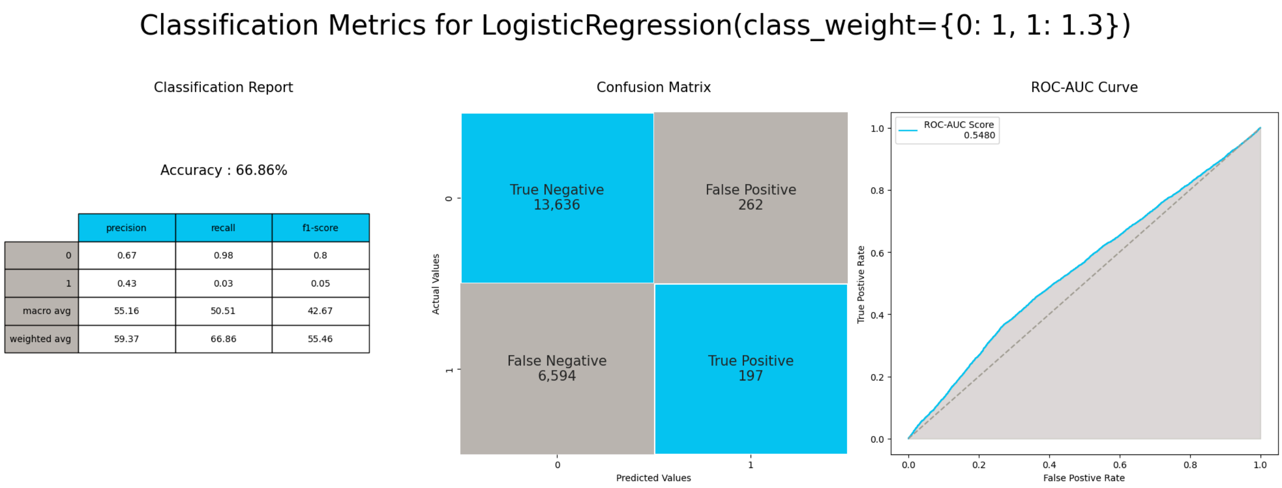
In [94]:
```
plt.figure(figsize=(20,8))

sns.heatmap(dummy_df.corr(), vmin=-1, annot=True, cmap="seismic")
```

Out[94]:
```
<Axes: >
```

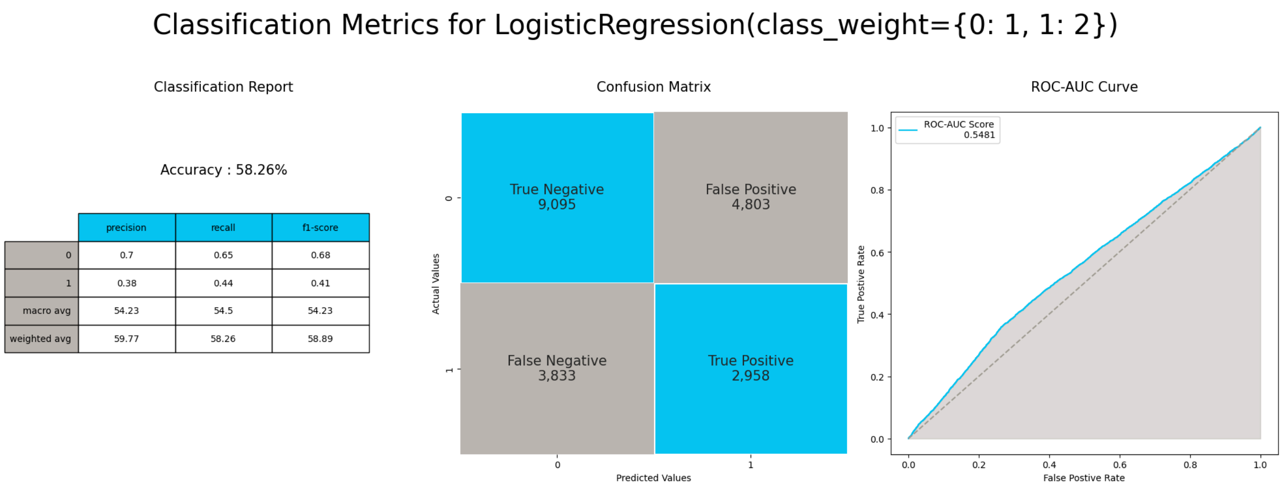


Logistic Regression with class weights

In [95]:
```
model = LogisticRegression(class_weight={0:1 , 1:1.3}).fit(x_train, y_train)
get_metrics(model, x_test, y_test)
```



In [96]:
```python
model = LogisticRegression(class_weight={0:1 , 1:2}).fit(x_train, y_train)
get_metrics(model, x_test, y_test)
```



Voting Classifier

In [97]:
```python
train_df = x_train.copy()
train_df["Depression"] = pd.DataFrame(y_train).reset_index(drop=True)["Depression"]
```

In [98]:
```python
D_1_df = train_df[train_df["Depression"] == 1]
```

In [99]:
```python
D_1_df.head(3)
```

Out[99]:

	Age	Income	Marital Status_Married	Marital Status_Single	Marital Status_Widowed	Number of Children_1	Number of Children_2	Number of Children_3	Number of Children_4	Smoking Status_Former	...	Employment Status_Unemployed	Alcohol Consumption_Low	Al Consumption_Moc
4	0.919355	0.047102	0	0	1	0	1	0	0	1	...	1	0	
6	0.225806	0.406555	1	0	0	0	0	1	0	0	...	0	0	
7	0.854839	0.067561	0	0	1	0	0	0	0	1	...	1	0	

3 rows × 23 columns

In [100…
```python
D_0_df = train_df[train_df["Depression"] == 0]
```

In [101…
```python
D_0_df.head(3)
```

Out[101…

	Age	Income	Marital Status_Married	Marital Status_Single	Marital Status_Widowed	Number of Children_1	Number of Children_2	Number of Children_3	Number of Children_4	Smoking Status_Former	...	Employment Status_Unemployed	Alcohol Consumption_Low	Al Consumption_Moc
0	0.500000	0.499308	1	0	0	1	0	0	0	0	...	0	0	
1	0.661290	0.116026	1	0	0	1	0	0	0	0	...	0	0	
2	0.967742	0.139655	1	0	0	0	0	1	0	0	...	0	0	

3 rows × 23 columns

In [102…
```python
D_1_df.shape, D_0_df.shape
```

Out[102…
```
((129416, 23), (263663, 23))
```

In [103…
```python
predicts = pd.DataFrame({"Actual":y_test})
models = pd.DataFrame()
list_of_models = dict()

for i in range(11):
```

```python
    D_1 = D_1_df.sample(frac=0.6, random_state=np.random.randint(1, 45781236))
    D_0 = D_0_df.sample(n=D_1.shape[0], random_state=np.random.randint(1, 45781236))
    mini_data = pd.concat([D_0, D_1]).sample(frac=1)
    mini_y_train = mini_data["Depression"]
    mini_x_train = mini_data.drop(columns="Depression")
    mini_model = XGBClassifier().fit(mini_x_train, mini_y_train)
    list_of_models[f"Model {i+1}"] = mini_model
    predicts[f"Model {i+1} Prediction"] = mini_model.predict(x_test)
    mets = precision_recall_fscore_support(y_test, mini_model.predict(x_test))
    models = models._append(
    {
        "Model":f"D_0_df{i+1}",
        "Precision_0":mets[0][0],
        "Precision_1":mets[0][1],
        "Recall_0":mets[1][0],
        "Recall_1":mets[1][1],
        "Accuracy":accuracy_score(y_test, mini_model.predict(x_test))
    }, ignore_index=True)
    print(f"..........Done Model {i+1}")
```

```
..........Done Model 1
..........Done Model 2
..........Done Model 3
..........Done Model 4
..........Done Model 5
..........Done Model 6
..........Done Model 7
..........Done Model 8
..........Done Model 9
..........Done Model 10
..........Done Model 11
```

In [104…

```python
predicts.head(3)
```

Out[104…

	Actual	Model 1 Prediction	Model 2 Prediction	Model 3 Prediction	Model 4 Prediction	Model 5 Prediction	Model 6 Prediction	Model 7 Prediction	Model 8 Prediction	Model 9 Prediction	Model 10 Prediction	Model 11 Prediction
366559	0	1	0	1	1	1	0	0	1	1	1	1
66432	1	0	1	1	1	1	1	1	1	1	1	1
243274	0	0	0	1	0	1	0	0	1	1	1	0

In [105…

```python
models
```

Out[105…

	Model	Precision_0	Precision_1	Recall_0	Recall_1	Accuracy
0	D_0_df1	0.677169	0.333492	0.496402	0.515683	0.502731
1	D_0_df2	0.677177	0.334957	0.557850	0.455750	0.524337
2	D_0_df3	0.678361	0.330788	0.281048	0.727286	0.427522
3	D_0_df4	0.679058	0.332516	0.373291	0.638934	0.460486
4	D_0_df5	0.666220	0.323353	0.465031	0.523192	0.484122
5	D_0_df6	0.677965	0.335712	0.551230	0.464144	0.522645
6	D_0_df7	0.667907	0.326042	0.361491	0.632160	0.450336
7	D_0_df8	0.687079	0.338231	0.403655	0.623767	0.475905
8	D_0_df9	0.680710	0.330133	0.176716	0.830364	0.391271
9	D_0_df10	0.668586	0.327267	0.233991	0.762627	0.407511
10	D_0_df11	0.677725	0.329236	0.144050	0.859814	0.378994

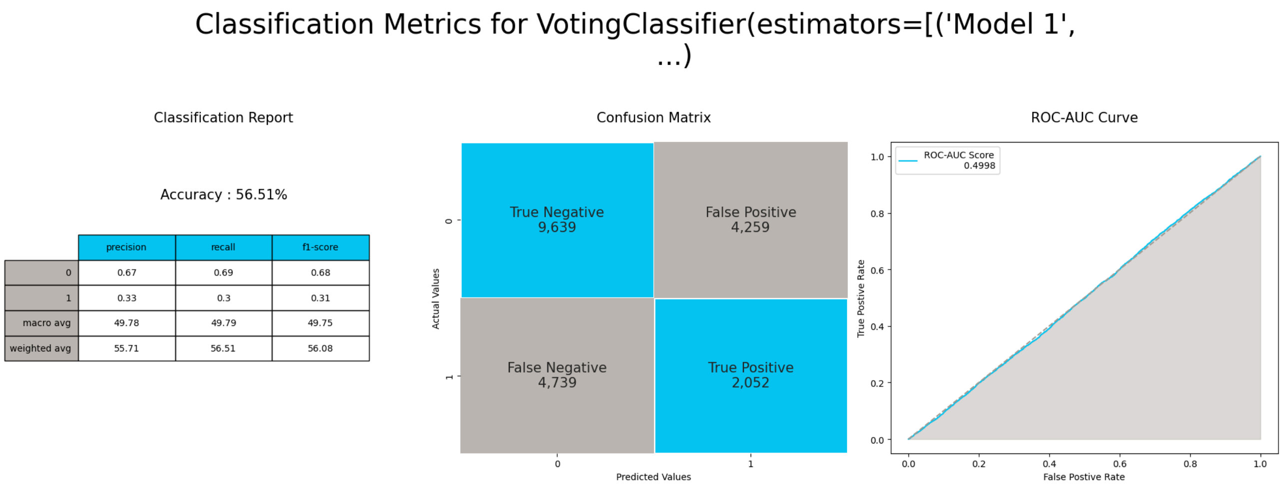
In [106…

```python
model = VotingClassifier(estimators=list(list_of_models.items()), voting="soft", verbose=True).fit(x_train, y_train)
```

```
[Voting] ................ (1 of 11) Processing Model 1, total=   0.6s
[Voting] ................ (2 of 11) Processing Model 2, total=   0.6s
[Voting] ................ (3 of 11) Processing Model 3, total=   0.6s
[Voting] ................ (4 of 11) Processing Model 4, total=   0.6s
[Voting] ................ (5 of 11) Processing Model 5, total=   0.6s
[Voting] ................ (6 of 11) Processing Model 6, total=   0.6s
[Voting] ................ (7 of 11) Processing Model 7, total=   0.7s
[Voting] ................ (8 of 11) Processing Model 8, total=   0.6s
[Voting] ................ (9 of 11) Processing Model 9, total=   0.6s
[Voting] .............. (10 of 11) Processing Model 10, total=   0.6s
[Voting] .............. (11 of 11) Processing Model 11, total=   0.7s
```

In [107…

```python
get_metrics(model, x_test, y_test)
```



SMOTE

In [108…
```
parquet_df["Depression"].value_counts()
```

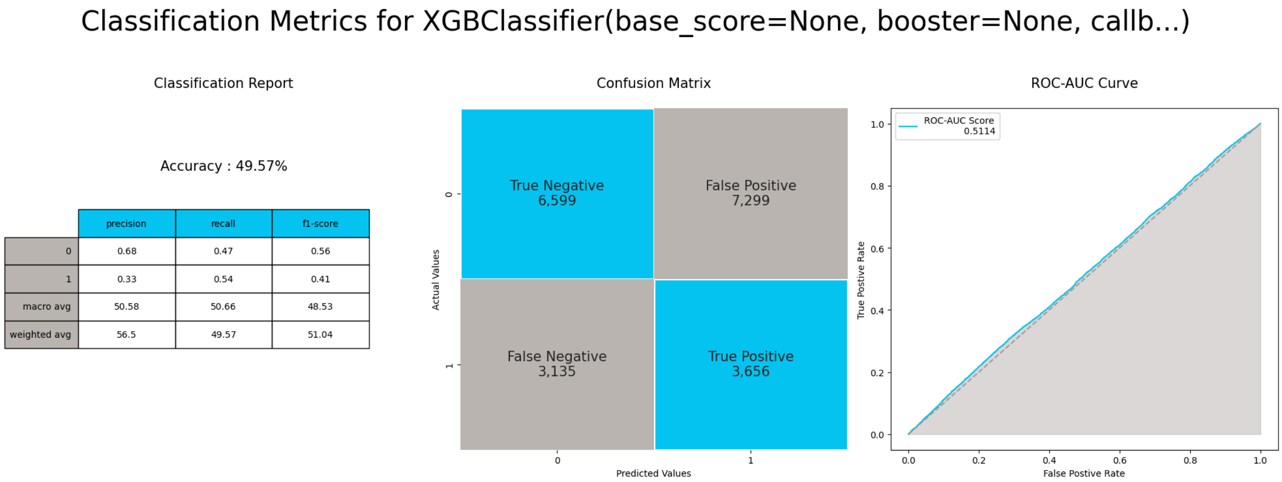
Out[108…
```
Depression
No     277561
Yes    136207
Name: count, dtype: int64
```

In [109…
```
from imblearn.over_sampling import SMOTE
```

In [110…
```
x_train_SMOTE, y_train_SMOTE = SMOTE(sampling_strategy={1:240451}, random_state=30, k_neighbors=1).fit_resample(x_train, y_train)
```

In [111…
```
model_SMOTE = XGBClassifier().fit(x_train_SMOTE, y_train_SMOTE)
```

In [112…
```
get_metrics(model_SMOTE, x_test, y_test)
```



Seperate Models for Numeric & Categorical

In [113…
```
num_df = parquet_df.select_dtypes(include='number')
```

In [114…
```
num_df.head()
```

Out[114…

	Age	Income
0	31	26265.67
1	55	42710.36
2	78	125332.79
3	58	9992.78
4	18	8595.08

In [ ]:
```
x_train, x_test, y_train, y_test = train_test_split(num_df.drop(columns="Depression"), num_df["Depression"], test_size=0.05, random_state=5)
```

In [ ]:
```
print(f'''
x_train shape : {x_train.shape}
x_test shape : {x_test.shape}
y_train shape : {y_train.shape}
y_test shape : {y_test.shape}
''')
```

In [ ]:
```
x_test.head()
```

In [ ]:
```
x_train, x_test = do_scaling(x_train, x_test)
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:
```
cat_df = parquet_df.select_dtypes(exclude='number')
cat_df = pd.concat([cat_df, parquet_df["Depression"]], axis=1)
```

In [ ]:
```
cat_df.head()
```

In [ ]: