Stroke Prediction

Introduction

- A stroke occurs when a blood vessel in the brain ruptures and bleeds, or when there's a blockage in the blood supply to the brain. The rupture or blockage prevents blood and oxygen from reaching the brain's tissues.
- Risk factors for stroke

Certain risk factors make you more susceptible to stroke. According to the National Heart, Lung, and Blood InstituteTrusted Source, the more risk factors you have, the more likely you are to have a stroke. Risk factors for stroke include:

Diet

An unhealthy diet that increases your risk of stroke is one that's high in:

```
salt
saturated fats
trans fats
cholesterol
```

Inactivity

Inactivity, or lack of exercise, can also raise your risk for stroke.

Regular exercise has a number of health benefits. The CDC recommends that adults get at least 2.5 hoursTrusted Source of aerobic exercise every week. This can mean simply a brisk walk a few times a week.

Alcohol consumption

Your risk for stroke also increases if you drink too much alcohol. Alcohol consumption should be done in moderation. This means no more than one drink per day for women, and no more than two for men. More than that may raise blood pressure levels as well as triglyceride levels, which can cause atherosclerosis.

Tobacco use

Using tobacco in any form also raises your risk for stroke, since it can damage your blood vessels and heart. This is further increased when smoking, because your blood pressure rises when you use nicotine. Personal background

There are certain personal risk factors for stroke that you can't control. Stroke risk can be linked to your:

```
Family history: Stroke risk is higher in some families because of genetic health issues, such as high blood pressure.
Sex: While both women and men can have strokes, they're more common in women than in men in all age groups.
Age: The older you are, the more likely you are to have a stroke.
Race and ethnicity: Caucasians, Asian Americans, and Hispanics are less likely to have a stroke than African-Americans, Alaska Natives, and American Indians.
```

Health history

Certain medical conditions are linked to stroke risk. These include:

```
a previous stroke or TIA
high blood pressure
high cholesterol
heart disorders, such as coronary artery disease
heart valve defects
enlarged heart chambers and irregular heartbeats
sickle cell disease
diabetes
```

Data

1. id: unique identifier
2. gender: "Male", "Female" or "Other"
3. age: age of the patient
4. hypertension: 0 if the patient doesn't have hypertension, 1 if the patient has hypertension
5. heart_disease: 0 if the patient doesn't have any heart diseases, 1 if the patient has a heart disease
6. ever_married: "No" or "Yes"
7. work_type: "children", "Govt_jov", "Never_worked", "Private" or "Self-employed"
8. Residence_type: "Rural" or "Urban"
9. avg_glucose_level: average glucose level in blood
10. bmi: body mass index
11. smoking_status: "formerly smoked", "never smoked", "smokes" or "Unknown"*
12. stroke: 1 if the patient had a stroke or 0 if not

Note: "Unknown" in smoking_status means that the information is unavailable for this patient

Importing Libraries and Data

In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from scipy.sparse import hstack
import seaborn as sns
sns.set()
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


from imblearn.over_sampling import RandomOverSampler

from sklearn.model_selection import train_test_split
from sklearn.linear_model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC
from sklearn.ensemble import RandomForestClassifier as rgb
from xgboost import XGBRFClassifier as xgb
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RandomizedSearchCV
from sklearn.preprocessing import MinMaxScaler
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import log_loss, confusion_matrix, accuracy_score

from sklearn.ensemble import StackingClassifier
from prettytable import PrettyTable, MSWORD_FRIENDLY, DEFAULT
```

In [2]:
```python
stroke = pd.read_csv("healthcare-dataset-stroke-data.csv")
```

In [3]:
```python
stroke.head()
```

Out[3]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stro
0	9046	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked	
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	NaN	never smoked	
2	31112	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never smoked	
3	60182	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smokes	
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never smoked	

In [4]:
```python
stroke.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5110 entries, 0 to 5109
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 5110 non-null   int64  
 1   gender             5110 non-null   object 
 2   age                5110 non-null   float64
 3   hypertension       5110 non-null   int64  
 4   heart_disease      5110 non-null   int64  
 5   ever_married       5110 non-null   object 
 6   work_type          5110 non-null   object 
 7   Residence_type     5110 non-null   object 
 8   avg_glucose_level  5110 non-null   float64
 9   bmi                4909 non-null   float64
 10  smoking_status     5110 non-null   object 
 11  stroke             5110 non-null   int64  
dtypes: float64(3), int64(4), object(5)
memory usage: 479.2+ KB
```

In [5]:
```python
stroke.describe()
```

Out[5]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	stroke
count	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	4909.000000	5110.000000
mean	36517.829354	43.226614	0.097456	0.054012	106.147677	28.893237	0.048728
std	21161.721625	22.612647	0.296607	0.226063	45.283560	7.854067	0.215320
min	67.000000	0.080000	0.000000	0.000000	55.120000	10.300000	0.000000
25%	17741.250000	25.000000	0.000000	0.000000	77.245000	23.500000	0.000000
50%	36932.000000	45.000000	0.000000	0.000000	91.885000	28.100000	0.000000
75%	54682.000000	61.000000	0.000000	0.000000	114.090000	33.100000	0.000000
max	72940.000000	82.000000	1.000000	1.000000	271.740000	97.600000	1.000000

In [6]:
```python
stroke.shape
```

Out[6]: (5110, 12)

Cleaning of Data

In [7]:
```python
stroke.isnull().sum()
```

Out[7]:
```
id                     0
gender                 0
age                    0
hypertension           0
heart_disease          0
ever_married           0
work_type              0
Residence_type         0
avg_glucose_level      0
bmi                  201
smoking_status         0
stroke                 0
dtype: int64
```

In [8]:
```python
stroke.bmi.replace(to_replace=np.nan, value=stroke.bmi.mean(), inplace=True)
```

In [9]:
```python
stroke.isnull().sum()
```

Out[9]:
```
id                   0
gender               0
age                  0
hypertension         0
heart_disease        0
ever_married         0
work_type            0
Residence_type       0
avg_glucose_level    0
bmi                  0
smoking_status       0
stroke               0
dtype: int64
```

Exploratory Data Analysis

In [10]:
```python
stroke.nunique()
```

Out[10]:
```
id                   5110
gender                  3
age                   104
hypertension            2
heart_disease           2
ever_married            2
work_type               5
Residence_type          2
avg_glucose_level    3979
bmi                   419
smoking_status          4
stroke                  2
dtype: int64
```

In [11]:
```python
stroke.stroke.value_counts()
```

Out[11]:
```
0    4861
1     249
Name: stroke, dtype: int64
```

Our data is imbalanced.

In [12]:
```python
stroke.gender.unique()
```

Out[12]: array(['Male', 'Female', 'Other'], dtype=object)

In [13]:
```python
stroke.hypertension.unique()
```

Out[13]: array([0, 1], dtype=int64)

In [14]:
```python
stroke.heart_disease.unique()
```

Out[14]: array([1, 0], dtype=int64)

In [15]:
```python
stroke.ever_married.unique()
```

Out[15]: array(['Yes', 'No'], dtype=object)

In [16]:
```python
stroke.work_type.unique()
```

Out[16]:
```
array(['Private', 'Self-employed', 'Govt_job', 'children', 'Never_worked'],
      dtype=object)
```

In [17]:
```python
stroke.Residence_type.unique()
```

Out[17]: array(['Urban', 'Rural'], dtype=object)

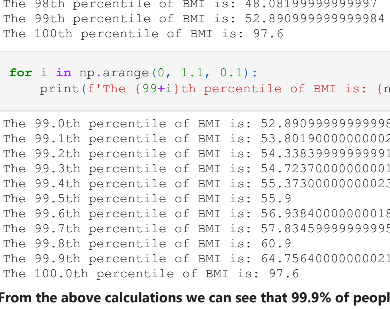
In [18]:
```python
stroke.smoking_status.unique()
```

Out[18]:
```
array(['formerly smoked', 'never smoked', 'smokes', 'Unknown'],
      dtype=object)
```

Univariate Analysis

Boxplot of bmi

In [19]:
```python
sns.boxplot(data=stroke, y='bmi')
plt.title('Boxplot of bmi')
plt.show()
```



In [20]:
```python
for i in range(0, 110, 10):
    print(f'The {i}th percentile of BMI is: {np.percentile(stroke.bmi, i)}')
```

```
The 0th percentile of BMI is: 10.3
The 10th percentile of BMI is: 19.890000000000004
The 20th percentile of BMI is: 22.7
The 30th percentile of BMI is: 24.8
The 40th percentile of BMI is: 26.699999999999996
The 50th percentile of BMI is: 28.4
The 60th percentile of BMI is: 29.5
The 70th percentile of BMI is: 31.6
The 80th percentile of BMI is: 34.3
The 90th percentile of BMI is: 38.7
The 100th percentile of BMI is: 97.6
```

In [21]:
```python
for i in range(90, 101, 1):
    print(f'The {i}th percentile of BMI is: {np.percentile(stroke.bmi, i)}')
```

```
The 90th percentile of BMI is: 38.7
The 91th percentile of BMI is: 39.3
The 92th percentile of BMI is: 40.0
The 93th percentile of BMI is: 40.8
The 94th percentile of BMI is: 41.7
The 95th percentile of BMI is: 42.65500000000002
The 96th percentile of BMI is: 43.8
The 97th percentile of BMI is: 45.1
The 98th percentile of BMI is: 48.08199999999997
The 99th percentile of BMI is: 52.890999999999984
The 100th percentile of BMI is: 97.6
```

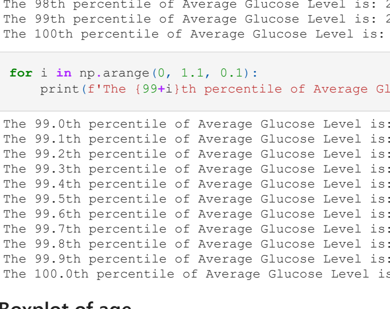
In [22]:
```python
for i in np.arange(0, 1.1, 0.1):
    print(f'The {99+i}th percentile of BMI is: {np.percentile(stroke.bmi, 99+i)}')
```

```
The 99.0th percentile of BMI is: 52.890999999999984
The 99.1th percentile of BMI is: 53.801900000000025
The 99.2th percentile of BMI is: 54.33839999999991
The 99.3th percentile of BMI is: 54.72370000000001
The 99.4th percentile of BMI is: 55.37300000000023
The 99.5th percentile of BMI is: 55.9
The 99.6th percentile of BMI is: 56.938400000000186
The 99.7th percentile of BMI is: 57.83459999999995
The 99.8th percentile of BMI is: 60.9
The 99.9th percentile of BMI is: 64.75640000000021
The 100.0th percentile of BMI is: 97.6
```

From the above calculations we can see that 99.9% of people have BMI less than 65.

Boxplot of Average Glucose Level

In [23]:
```python
sns.boxplot(data=stroke, y='avg_glucose_level')
plt.title('Boxplot of avg_glucose_level')
plt.show()
```



In [24]:
```python
for i in range(0, 110, 10):
    print(f'The {i}th percentile of Average Glucose Level is: {np.percentile(stroke.avg_glucose_level, i)}')
```

```
The 0th percentile of Average Glucose Level is: 55.12
The 10th percentile of Average Glucose Level is: 65.789
The 20th percentile of Average Glucose Level is: 73.76
The 30th percentile of Average Glucose Level is: 80.03800000000001
The 40th percentile of Average Glucose Level is: 85.6
The 50th percentile of Average Glucose Level is: 91.88499999999999
The 60th percentile of Average Glucose Level is: 98.914
The 70th percentile of Average Glucose Level is: 108.51599999999999
The 80th percentile of Average Glucose Level is: 124.16
The 90th percentile of Average Glucose Level is: 192.1810000000001
The 100th percentile of Average Glucose Level is: 271.74
```

In [25]:
```python
for i in range(90, 101):
    print(f'The {i}th percentile of Average Glucose Level is: {np.percentile(stroke.avg_glucose_level, i)}')
```

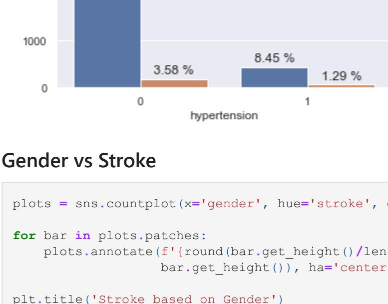
```
The 90th percentile of Average Glucose Level is: 192.1810000000001
The 91th percentile of Average Glucose Level is: 197.54760000000002
The 92th percentile of Average Glucose Level is: 202.1020000000001
The 93th percentile of Average Glucose Level is: 206.43329999999997
The 94th percentile of Average Glucose Level is: 210.9546
The 95th percentile of Average Glucose Level is: 216.29450000000003
The 96th percentile of Average Glucose Level is: 220.14279999999985
The 97th percentile of Average Glucose Level is: 226.86919999999998
The 98th percentile of Average Glucose Level is: 231.91579999999993
The 99th percentile of Average Glucose Level is: 240.7082
The 100th percentile of Average Glucose Level is: 271.74
```

In [26]:
```python
for i in np.arange(0, 1.1, 0.1):
    print(f'The {99+i}th percentile of Average Glucose Level is: {np.percentile(stroke.avg_glucose_level, 99
```

```
The 99.0th percentile of Average Glucose Level is: 240.7082
The 99.1th percentile of Average Glucose Level is: 242.62418000000005
The 99.2th percentile of Average Glucose Level is: 243.5364
The 99.3th percentile of Average Glucose Level is: 244.78348000000017
The 99.4th percentile of Average Glucose Level is: 247.7522800000001
The 99.5th percentile of Average Glucose Level is: 249.29909999999998
The 99.6th percentile of Average Glucose Level is: 251.53896000000003
The 99.7th percentile of Average Glucose Level is: 253.90711
The 99.8th percentile of Average Glucose Level is: 256.3977400000002
The 99.9th percentile of Average Glucose Level is: 263.5338400000001
The 100.0th percentile of Average Glucose Level is: 271.74
```

Boxplot of age

In [27]:
```python
sns.boxplot(data=stroke, y='age')
plt.title('Boxplot of age')
plt.show()
```

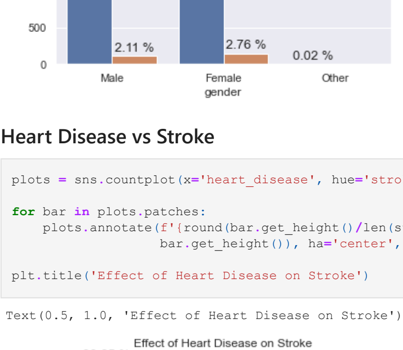


Bivariate Analysis

Hypertension vs Stroke

In [28]:
```python
plots = sns.countplot(x='hypertension', hue='stroke', data=stroke)

for bar in plots.patches:
    plots.annotate(f'{round(bar.get_height()/len(stroke)*100,2)} %', xy=(bar.get_x() + bar.get_width() / 2,
                   bar.get_height()), ha='center', va='center', size=13, xytext=(0, 8), textcoords='offset p


plt.title('Effect of Hypertension on Stroke')
```

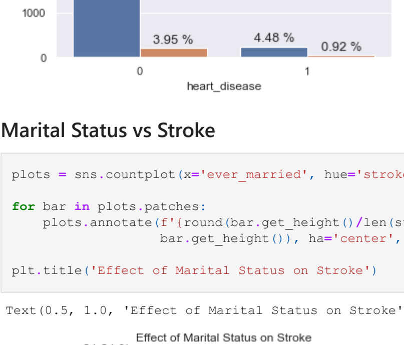
Out[28]: Text(0.5, 1.0, 'Effect of Hypertension on Stroke')



Gender vs Stroke

In [29]:
```python
plots = sns.countplot(x='gender', hue='stroke', data=stroke)

for bar in plots.patches:
    plots.annotate(f'{round(bar.get_height()/len(stroke)*100,2)} %', xy=(bar.get_x() + bar.get_width() / 2,
                   bar.get_height()), ha='center', va='center', size=13, xytext=(0, 8), textcoords='offset p

plt.title('Stroke based on Gender')
```

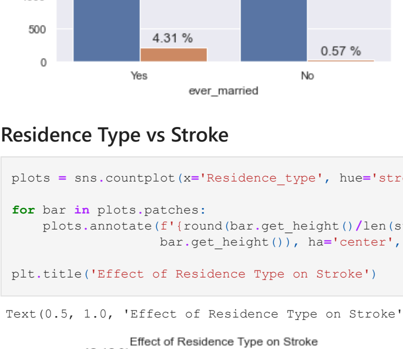
Out[29]: Text(0.5, 1.0, 'Stroke based on Gender')



Heart Disease vs Stroke

In [30]:
```python
plots = sns.countplot(x='heart_disease', hue='stroke', data=stroke)

for bar in plots.patches:
    plots.annotate(f'{round(bar.get_height()/len(stroke)*100,2)} %', xy=(bar.get_x() + bar.get_width() / 2,
                   bar.get_height()), ha='center', va='center', size=13, xytext=(0, 8), textcoords='offset p

plt.title('Effect of Heart Disease on Stroke')
```

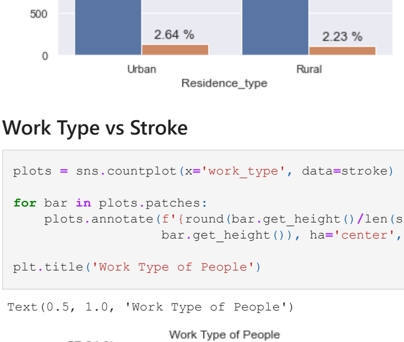
Out[30]: Text(0.5, 1.0, 'Effect of Heart Disease on Stroke')



Marital Status vs Stroke

In [31]:
```python
plots = sns.countplot(x='ever_married', hue='stroke', data=stroke)

for bar in plots.patches:
    plots.annotate(f'{round(bar.get_height()/len(stroke)*100,2)} %', xy=(bar.get_x() + bar.get_width() / 2,
                   bar.get_height()), ha='center', va='center', size=13, xytext=(0, 8), textcoords='offset p

plt.title('Effect of Marital Status on Stroke')
```

Out[31]: Text(0.5, 1.0, 'Effect of Marital Status on Stroke')



Residence Type vs Stroke

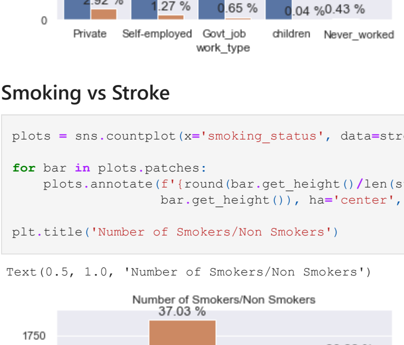
In [32]:
```python
plots = sns.countplot(x='Residence_type', hue='stroke', data=stroke)

for bar in plots.patches:
    plots.annotate(f'{round(bar.get_height()/len(stroke)*100,2)} %', xy=(bar.get_x() + bar.get_width() / 2,
                   bar.get_height()), ha='center', va='center', size=13, xytext=(0, 8), textcoords='offset p

plt.title('Effect of Residence Type on Stroke')
```

Out[32]: Text(0.5, 1.0, 'Effect of Residence Type on Stroke')

Work Type vs Stroke

In [33]:
```python
plots = sns.countplot(x='work_type', data=stroke)

for bar in plots.patches:
    plots.annotate(f'{round(bar.get_height()/len(stroke)*100,2)} %', xy=(bar.get_x() + bar.get_width() / 2,
                   bar.get_height()), ha='center', va='center', size=13, xytext=(0, 8), textcoords='offset p

plt.title('Work Type of People')
```

Out[33]: Text(0.5, 1.0, 'Work Type of People')



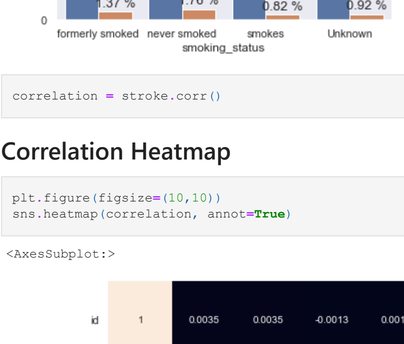
In [34]:
```python
plots = sns.countplot(x='work_type', hue='stroke', data=stroke)

for bar in plots.patches:
    plots.annotate(f'{round(bar.get_height()/len(stroke)*100,2)} %', xy=(bar.get_x() + bar.get_width() / 2,
                   bar.get_height()), ha='center', va='center', size=13, xytext=(0, 8), textcoords='offset p

plt.title('Effect of Work Type on Stroke')
```

Out[34]: Text(0.5, 1.0, 'Effect of Work Type on Stroke')

Smoking vs Stroke

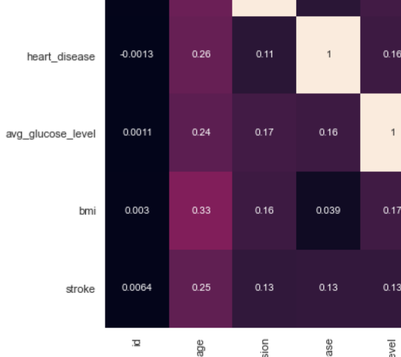
In [35]:
```python
plots = sns.countplot(x='smoking_status', data=stroke)

for bar in plots.patches:
    plots.annotate(f'{round(bar.get_height()/len(stroke)*100,2)} %', xy=(bar.get_x() + bar.get_width() / 2,
                   bar.get_height()), ha='center', va='center', size=13, xytext=(0, 8), textcoords='offset p

plt.title('Number of Smokers/Non Smokers')
```

Out[35]: Text(0.5, 1.0, 'Number of Smokers/Non Smokers')



In [36]:
```python
plots = sns.countplot(x='smoking_status', hue='stroke', data=stroke)

for bar in plots.patches:
    plots.annotate(f'{round(bar.get_height()/len(stroke)*100,2)} %', xy=(bar.get_x() + bar.get_width() / 2,
                   bar.get_height()), ha='center', va='center', size=13, xytext=(0, 8), textcoords='offset p

plt.title('Effect of Smoking on Stroke')
```

Out[36]: Text(0.5, 1.0, 'Effect of Smoking on Stroke')

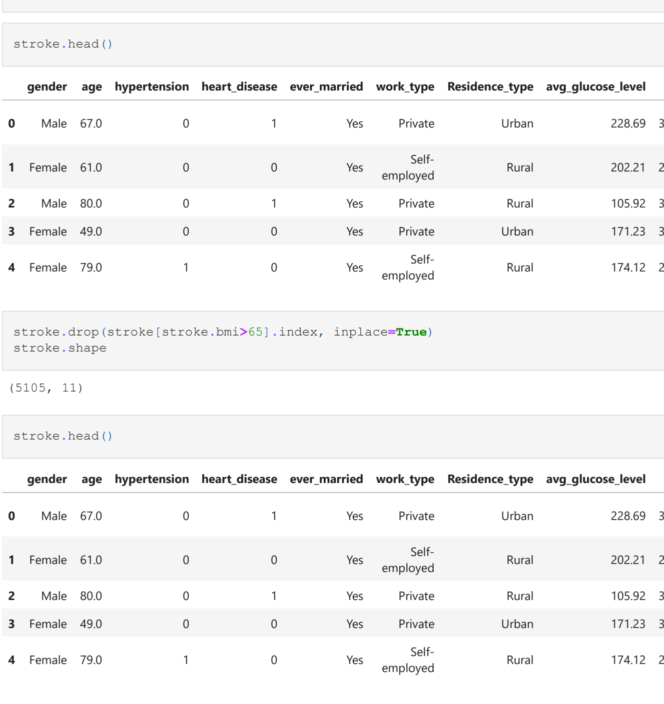


In [37]:
```python
correlation = stroke.corr()
```

Correlation Heatmap

In [38]:
```python
plt.figure(figsize=(10,10))
sns.heatmap(correlation, annot=True)
```

Out[38]: <AxesSubplot:>



Removing Outliers and Redundant Columns

In [39]:
```python
stroke.drop(labels='id', axis=1, inplace=True)
```

In [40]:
```python
stroke.head()
```

Out[40]:

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	Male	67.0	0	1	Yes	Private	Urban	228.69	36.600000	formerly smoked	1
1	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	28.893237	never smoked	1
2	Male	80.0	0	1	Yes	Private	Rural	105.92	32.500000	never smoked	1
3	Female	49.0	0	0	Yes	Private	Urban	171.23	34.400000	smokes	1
4	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.000000	never smoked	1

In [41]:
```python
stroke.drop(stroke[stroke.bmi>65].index, inplace=True)
stroke.shape
```

Out[41]: (5105, 11)

In [42]:
```python
stroke.head()
```

Out[42]:

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	Male	67.0	0	1	Yes	Private	Urban	228.69	36.600000	formerly smoked	1
1	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	28.893237	never smoked	1
2	Male	80.0	0	1	Yes	Private	Rural	105.92	32.500000	never smoked	1
3	Female	49.0	0	0	Yes	Private	Urban	171.23	34.400000	smokes	1
4	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.000000	never smoked	1

Machine Learning Models

Splitting The Dataset

Splitting the dataset into train and test in 80:20.

In [43]:
```python
x = stroke.iloc[:,:-1]
y = stroke.iloc[:,-1]
```

In [44]:
```python
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, stratify=y)
x_train, x_cv, y_train, y_cv = train_test_split(x_train, y_train, test_size=0.2, stratify=y_train)
```

In [45]:
```python
x_train.shape
```

Out[45]: (3267, 10)

In [46]:
```python
x_test.shape
```

Out[46]: (1021, 10)

In [47]:
```python
y_train.value_counts()
```

Out[47]:
```
0    3108
1     159
Name: stroke, dtype: int64
```

In [48]:
```python
rom = RandomOverSampler(random_state=42)
x_train, y_train = rom.fit_resample(x_train, y_train)
```

In [49]:
```python
x_train.shape
```

Out[49]: (6216, 10)

In [50]:
```python
y_train.value_counts()
```

Out[50]:
```
0    3108
1    3108
Name: stroke, dtype: int64
```

One-Hot Encoding of Categorical Data

In [51]:
```python
ohe = ColumnTransformer([('ohe', OneHotEncoder(handle_unknown='ignore'), ['gender', 'ever_married', 'work_ty
ohe.fit(x_train)
print(x_train.shape, y_train.shape)

x_train_ohe = ohe.transform(x_train)
x_cv_ohe = ohe.transform(x_cv)
x_test_ohe = ohe.transform(x_test)

print('After Vectorization......')
print(x_train_ohe.shape, y_train.shape)
print(x_cv_ohe.shape, y_cv.shape)
print(x_test_ohe.shape, y_test.shape)
```

```
(6216, 10) (6216,)
After Vectorization......
(6216, 21) (6216,)
(817, 21) (817,)
(1021, 21) (1021,)
```

In [52]:
```python
x_train_ohe = x_train_ohe[:, :16]
x_cv_ohe = x_cv_ohe[:, :16]
x_test_ohe = x_test_ohe[:, :16]

print('After Vectorization......')
print(x_train_ohe.shape, y_train.shape)
print(x_cv_ohe.shape, y_cv.shape)
print(x_test_ohe.shape, y_test.shape)
```

```
After Vectorization......
(6216, 16) (6216,)
(817, 16) (817,)
(1021, 16) (1021,)
```

In [53]:
```python
features = ohe.get_feature_names()
features
```

Out[53]:
```
['ohe__x0_Female',
 'ohe__x0_Male',
 'ohe__x0_Other',
 'ohe__x1_No',
 'ohe__x1_Yes',
 'ohe__x2_Govt_job',
 'ohe__x2_Never_worked',
 'ohe__x2_Private',
 'ohe__x2_Self-employed',
 'ohe__x2_children',
 'ohe__x3_Rural',
 'ohe__x3_Urban',
 'ohe__x4_Unknown',
 'ohe__x4_formerly smoked',
 'ohe__x4_never smoked',
 'ohe__x4_smokes',
 'age',
 'hypertension',
 'heart_disease',
 'avg_glucose_level',
 'bmi']
```

In [54]:
```python
x_train_hyp = np.array(x_train['hypertension']).reshape((-1,1))
x_cv_hyp = np.array(x_cv['hypertension']).reshape((-1,1))
x_test_hyp = np.array(x_test['hypertension']).reshape((-1,1))

print('After Vectorization......')
print(x_train_hyp.shape, y_train.shape)
print(x_cv_hyp.shape, y_cv.shape)
print(x_test_hyp.shape, y_test.shape)
```

```
After Vectorization......
(6216, 1) (6216,)
(817, 1) (817,)
(1021, 1) (1021,)
```

In [55]:
```python
x_train_hd = np.array(x_train['heart_disease']).reshape((-1,1))
x_cv_hd = np.array(x_cv['heart_disease']).reshape((-1,1))
x_test_hd = np.array(x_test['heart_disease']).reshape((-1,1))

print('After Vectorization......')
print(x_train_hd.shape, y_train.shape)
print(x_cv_hd.shape, y_cv.shape)
print(x_test_hd.shape, y_test.shape)
```

```
After Vectorization......
(6216, 1) (6216,)
(817, 1) (817,)
(1021, 1) (1021,)
```

In [56]:
```python
std = ColumnTransformer([('norm', MinMaxScaler(), ['age', 'avg_glucose_level', 'bmi'])], remainder='drop')
std.fit(x_train)
print(x_train.shape, y_train.shape)

x_train_std = std.transform(x_train)
x_cv_std = std.transform(x_cv)
x_test_std = std.transform(x_test)

print('After Vectorization......')
print(x_train_std.shape, y_train.shape)
print(x_cv_std.shape, y_cv.shape)
print(x_test_std.shape, y_test.shape)
```

```
(6216, 10) (6216,)
After Vectorization......
(6216, 3) (6216,)
(817, 3) (817,)
(1021, 3) (1021,)
```

Combining all encoded columns

In [57]:
```python
x_tr = np.hstack((x_train_ohe.astype(np.float), x_train_hyp.astype(np.float), x_train_hd.astype(np.float), x
x_cv = np.hstack((x_cv_ohe.astype(np.float), x_cv_hyp.astype(np.float), x_cv_hd.astype(np.float), x_cv_std.a
x_te = np.hstack((x_test_ohe.astype(np.float), x_test_hyp.astype(np.float), x_test_hd.astype(np.float), x_te

print("Final Data Matrix Shape is........")
print(x_tr.shape,y_train.shape)
print(x_cv.shape,y_cv.shape)
print(x_te.shape,y_test.shape)
```

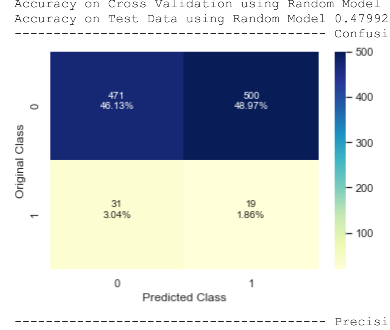
```
Final Data Matrix Shape is........
(6216, 21) (6216,)
(817, 21) (817,)
(1021, 21) (1021,)
```

In [58]:
```python
def cnf_matrix(true_y, pred_y):

    cf_matrix = confusion_matrix(y_test, predicted_y)
    print('-'*40, 'Confusion Matrix', '-'*40)
    group_counts = ['{0:0.0f}'.format(value) for value in cf_matrix.flatten()]
    group_percentages = ['{0:.2%}'.format(value) for value in cf_matrix.flatten()/np.sum(cf_matrix)]
    labels = [f'{v1}\n{v2}\n' for v1, v2 in zip(group_counts,group_percentages)]
    labels = np.asarray(labels).reshape(2,2)
    sns.heatmap(cf_matrix, annot=labels, fmt='', cmap="YlGnBu")
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()

    # Precision Matrix
    pc_matrix =(cf_matrix/cf_matrix.sum(axis=0))
    print("-"*40, "Precision matrix (Columm Sum=1)", "-"*40)
    sns.heatmap(pc_matrix, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=[0,1], yticklabels=[0,1])
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()

    # Recall Matrix
    rl_matrix =(((cf_matrix.T)/(cf_matrix.sum(axis=1))).T)
    print("-"*40, "Recall matrix (Row sum=1)", "-"*40)
    sns.heatmap(rl_matrix, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=[0,1], yticklabels=[0,1])
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
```

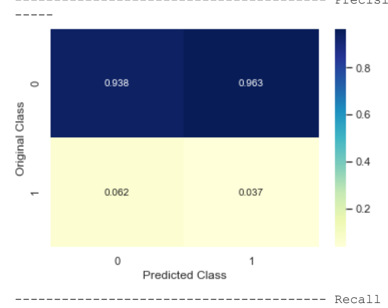
Random Model and its Performance

In [59]:
```python
test_data_len = x_test.shape[0]
cv_data_len = x_cv.shape[0]

# we create a output array that has exactly same size as the CV data
cv_predicted_y = np.zeros((cv_data_len,2))
for i in range(cv_data_len):
    rand_probs = np.random.rand(1,2)
    cv_predicted_y[i] = ((rand_probs/sum(sum(rand_probs)))[0])

# Test-Set error.
# We create a output array that has exactly same as the test data
test_predicted_y = np.zeros((test_data_len,2))
for i in range(test_data_len):
    rand_probs = np.random.rand(1,2)
    test_predicted_y[i] = ((rand_probs/sum(sum(rand_probs)))[0])

predicted_y = np.argmax(test_predicted_y, axis=1)
predicted_cv = np.argmax(cv_predicted_y, axis=1)


ll_rm_cv = log_loss(y_cv,cv_predicted_y, eps=1e-15)
ac_rm_cv = accuracy_score(y_cv, predicted_cv)
ll_rm_te = log_loss(y_test,test_predicted_y, eps=1e-15)
ac_rm_te = accuracy_score(y_test, predicted_y)

print("Log loss on Cross Validation Data using Random Model",ll_rm_cv)
print("Log loss on Test Data using Random Model",ll_rm_te)
print('Accuracy on Cross Validation using Random Model', ac_rm_cv)
print('Accuracy on Test Data using Random Model', ac_rm_te)

cnf_matrix(y_test, predicted_y)
```

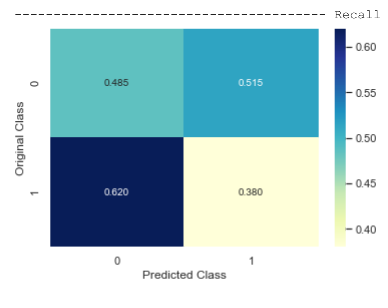
```
Log loss on Cross Validation Data using Random Model 0.9264253972091854
Log loss on Test Data using Random Model 0.9332675901969544
Accuracy on Cross Validation using Random Model 0.4614443084455324
Accuracy on Test Data using Random Model 0.47992164544564153
---------------------------------------- Confusion Matrix ----------------------------------------
```




```
---------------------------------------- Precision matrix (Columm Sum=1) ----------------------------------------
```




```
---------------------------------------- Recall matrix (Row sum=1) ----------------------------------------
```



Logistic Regression

Hyperparameter Tuning

In [60]:
```python
alpha = [10 ** x for x in range(-6, 4)]
params = {'alpha':alpha}
clf1 = SGDClassifier(loss='log', n_jobs=-1, random_state=42)
r_search = RandomizedSearchCV(clf1, param_distributions=params, return_train_score=True, random_state=42)
r_search.fit(x_tr, y_train)
```

Out[60]:
```
RandomizedSearchCV(estimator=SGDClassifier(loss='log', n_jobs=-1,
                                           random_state=42),
                   param_distributions={'alpha': [1e-06, 1e-05, 0.0001, 0.001,
                                                  0.01, 0.1, 1, 10, 100,
                                                  1000]},
                   random_state=42, return_train_score=True)
```

In [61]:
```python
print(f'The best hyperparameter values is {r_search.best_params_} at which the score is {r_search.best_score
```

```
The best hyperparameter values is {'alpha': 0.001} at which the score is 0.7689837365775675
```

Training the model

In [62]:
```python
clf1 = SGDClassifier(loss='log', n_jobs=-1, random_state=42, **r_search.best_params_)
clf1.fit(x_tr, y_train)
cal_clf1 = CalibratedClassifierCV(clf1, cv='prefit')
cal_clf1.fit(x_tr, y_train)
```

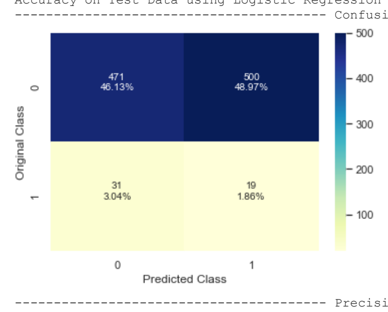
Out[62]:
```
CalibratedClassifierCV(base_estimator=SGDClassifier(alpha=0.001, loss='log',
                                                    n_jobs=-1,
                                                    random_state=42),
                       cv='prefit')
```

In [63]:
```python
y_pred_cv = cal_clf1.predict(x_cv)
y_prob_cv = cal_clf1.predict_proba(x_cv)
y_pred = cal_clf1.predict(x_te)
y_prob = cal_clf1.predict_proba(x_te)
```

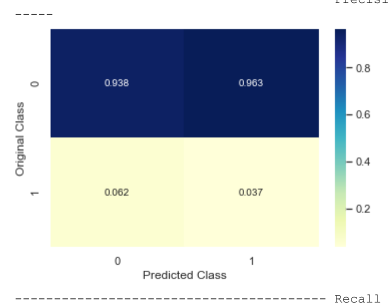
Performance of the model

In [64]:
```python
ll_lg_cv = log_loss(y_cv, y_prob_cv, eps=1e-15)
ac_lg_cv = accuracy_score(y_cv, y_pred_cv)
ll_lg_te = log_loss(y_test, y_prob, eps=1e-15)
ac_lg_te = accuracy_score(y_test, y_pred)


print("Log loss on Cross Validation Data using Logistic Regression",ll_lg_cv)
print("Log loss on Test Data using Logistic Regression",ll_lg_te)
print('Accuracy on Cross Validation using Logistic Regression', ac_lg_cv)
print('Accuracy on Test Data using Logistic Regression', ac_lg_te)

cnf_matrix(y_test, y_pred)
```

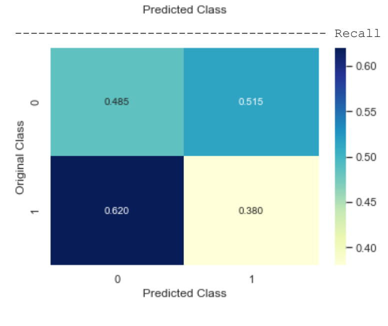
```
Log loss on Cross Validation Data using Logistic Regression 0.5125195612125583
Log loss on Test Data using Logistic Regression 0.5231360585054503
Accuracy on Cross Validation using Logistic Regression 0.7490820073439413
Accuracy on Test Data using Logistic Regression 0.732615083251714
---------------------------------------- Confusion Matrix ----------------------------------------
```




```
---------------------------------------- Precision matrix (Columm Sum=1) ----------------------------------------
```



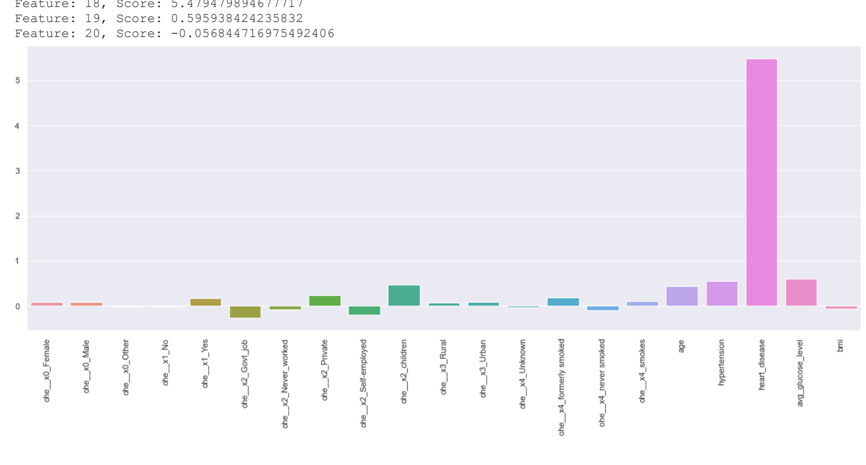

```
---------------------------------------- Recall matrix (Row sum=1) ----------------------------------------
```



Feature Importance

In [65]:
```python
importance = clf1.coef_
# summarize feature importance
for i,v in enumerate(importance[0]):
    print(f'Feature: {i}, Score: {v}')

plt.figure(figsize=(20,7))
sns.barplot(x=[x for x in range(importance.shape[1])], y=importance[0]).set_xticklabels(features, rotation=9
plt.show()
```

```
Feature: 0, Score: 0.08744457495307384
Feature: 1, Score: 0.08111951641250333
Feature: 2, Score: -0.018148049134373182
Feature: 3, Score: -0.017645247504174698
Feature: 4, Score: 0.16806128973537904
Feature: 5, Score: -0.264252568149695
Feature: 6, Score: -0.08060563419806256
Feature: 7, Score: 0.2271032318359398
Feature: 8, Score: -0.2002913243679036
Feature: 9, Score: 0.4684623371109256
Feature: 10, Score: 0.06417623241019317
Feature: 11, Score: 0.08623980982100894
Feature: 12, Score: -0.02709757925860014
Feature: 13, Score: 0.17847072939278436
Feature: 14, Score: -0.0979924720277727
Feature: 15, Score: 0.0970353641247913
Feature: 16, Score: 0.4312492605722929
Feature: 17, Score: 0.5463021567882967
Feature: 18, Score: 5.479479894677717
Feature: 19, Score: 0.595938424235832
Feature: 20, Score: -0.056844716975492406
```



Support Vector Machines

Hyperparameter Tuning

In [66]:
```python
alpha = [10 ** x for x in range(-6, 4)]
params = {'alpha':alpha}
clf2 = SGDClassifier(loss='hinge', n_jobs=-1, random_state=42)
r_search = RandomizedSearchCV(clf2, param_distributions=params, return_train_score=True, random_state=42)
r_search.fit(x_tr, y_train)
```

Out[66]:
```
RandomizedSearchCV(estimator=SGDClassifier(n_jobs=-1, random_state=42),
                   param_distributions={'alpha': [1e-06, 1e-05, 0.0001, 0.001,
                                                  0.01, 0.1, 1, 10, 100,
                                                  1000]},
                   random_state=42, return_train_score=True)
```

In [67]:
```python
print(f'The best hyperparameter values is {r_search.best_params_} at which the score is {r_search.best_score
```

```
The best hyperparameter values is {'alpha': 0.0001} at which the score is 0.7747760448867355
```

Training the model

In [68]:
```python
clf2 = SGDClassifier(loss='hinge', n_jobs=-1, random_state=42, **r_search.best_params_)
clf2.fit(x_tr, y_train)
cal_clf2 = CalibratedClassifierCV(clf2, cv='prefit')
cal_clf2.fit(x_tr, y_train)
```

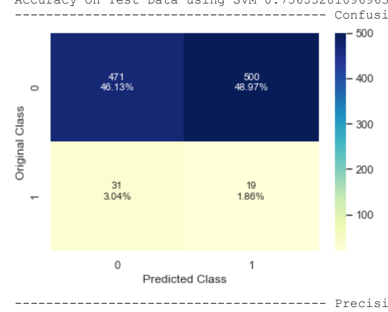
Out[68]:
```
CalibratedClassifierCV(base_estimator=SGDClassifier(n_jobs=-1, random_state=42),
                       cv='prefit')
```

In [69]:
```python
y_pred_cv = cal_clf2.predict(x_cv)
y_prob_cv = cal_clf2.predict_proba(x_cv)
y_pred = cal_clf2.predict(x_te)
y_prob = cal_clf2.predict_proba(x_te)
```

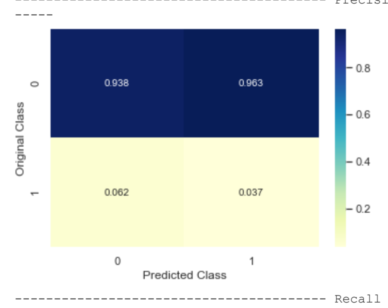
Performance of the model

In [70]:
```python
ll_svm_cv = log_loss(y_cv, y_prob_cv, eps=1e-15)
ac_svm_cv = accuracy_score(y_cv, y_pred_cv)
ll_svm_te = log_loss(y_test, y_prob, eps=1e-15)
ac_svm_te = accuracy_score(y_test, y_pred)


print("Log loss on Cross Validation Data using SVM",ll_svm_cv)
print("Log loss on Test Data using SVM",ll_svm_te)
print('Accuracy on Cross Validation using SVM', ac_svm_cv)
print('Accuracy on Test Data using SVM', ac_svm_te)

cnf_matrix(y_test, y_pred)
```

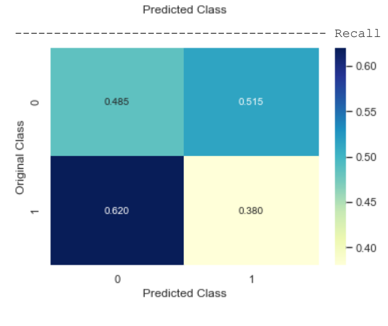
```
Log loss on Cross Validation Data using SVM 0.5183016042379512
Log loss on Test Data using SVM 0.5358896940741728
Accuracy on Cross Validation using SVM 0.7429620563035496
Accuracy on Test Data using SVM 0.7365328109696376
---------------------------------------- Confusion Matrix ----------------------------------------
```




```
---------------------------------------- Precision matrix (Columm Sum=1) ----------------------------------------
```



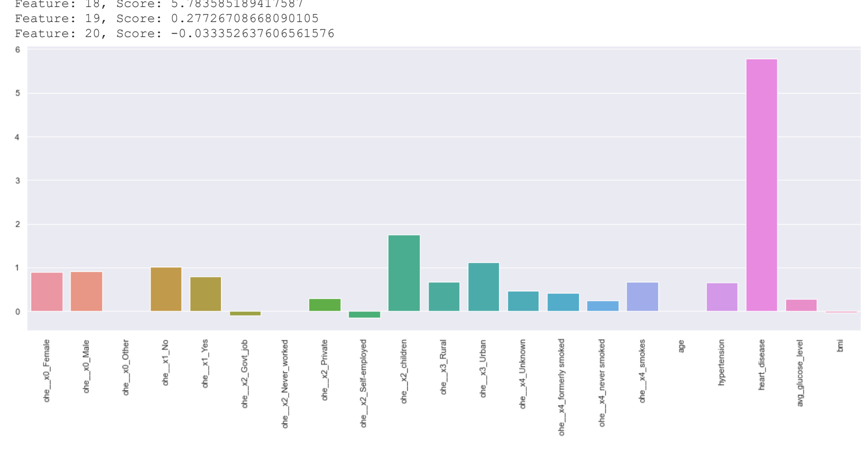

```
---------------------------------------- Recall matrix (Row sum=1) ----------------------------------------
```



Feature Importance

In [71]:
```python
importance = clf2.coef_
# summarize feature importance
for i,v in enumerate(importance[0]):
    print(f'Feature: {i}, Score: {v}')

plt.figure(figsize=(20,7))
sns.barplot(x=[x for x in range(importance.shape[1])], y=importance[0]).set_xticklabels(features, rotation=9
plt.show()
```

```
Feature: 0, Score: 0.891098813947435
Feature: 1, Score: 0.9208021077456798
Feature: 2, Score: 0.0
Feature: 3, Score: 1.009911989140427
Feature: 4, Score: 0.8019889325526858
Feature: 5, Score: -0.0891098813947417
Feature: 6, Score: 0.0
Feature: 7, Score: 0.29703293798247765
Feature: 8, Score: -0.14851646899123905
Feature: 9, Score: 1.7524943340966257
Feature: 10, Score: 0.683175757359692
Feature: 11, Score: 1.128725164333421
Feature: 12, Score: 0.47525270077196574
Feature: 13, Score: 0.4158461131754637
Feature: 14, Score: 0.23762635038598182
Feature: 15, Score: 0.6831757573597056
Feature: 16, Score: -1.3947300287990333e-14
Feature: 17, Score: 0.6534724635614665
Feature: 18, Score: 5.783585189417587
Feature: 19, Score: 0.27726708668090105
Feature: 20, Score: -0.033352637606561576
```



Naive Bayes

Hyperparameter Tuning

In [72]:
```python
alpha = [0.0000001,0.000001,0.00001,0.0001,0.001,0.01,0.1,1,10,50,100]
params = {'alpha':alpha}
clf3 = MultinomialNB()
r_search = RandomizedSearchCV(clf3, param_distributions=params, return_train_score=True, random_state=42)
r_search.fit(x_tr, y_train)
```

Out[72]:
```
RandomizedSearchCV(estimator=MultinomialNB(),
                   param_distributions={'alpha': [1e-07, 1e-06, 1e-05, 0.0001,
                                                  0.001, 0.01, 0.1, 1, 10, 50,
                                                  100]},
                   random_state=42, return_train_score=True)
```

In [73]:
```python
print(f'The best hyperparameter values is {r_search.best_params_} at which the score is {r_search.best_score
```

```
The best hyperparameter values is {'alpha': 0.01} at which the score is 0.6703707967188602
```

Training the model

In [74]:
```python
clf3 = MultinomialNB(**r_search.best_params_)
clf3.fit(x_tr, y_train)
cal_clf3 = CalibratedClassifierCV(clf3, cv='prefit')
cal_clf3.fit(x_tr, y_train)
```

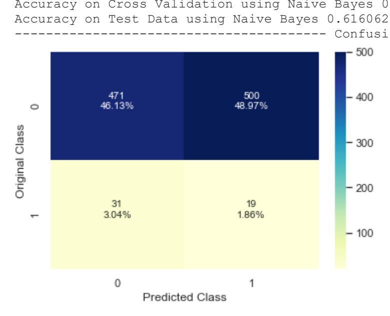
Out[74]:
```
CalibratedClassifierCV(base_estimator=MultinomialNB(alpha=0.01), cv='prefit')
```

In [75]:
```python
y_pred_cv = cal_clf3.predict(x_cv)
y_prob_cv = cal_clf3.predict_proba(x_cv)
y_pred = cal_clf3.predict(x_te)
y_prob = cal_clf3.predict_proba(x_te)
```

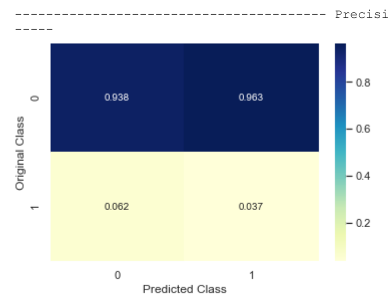
Performance of the model

In [76]:
```python
ll_nb_cv = log_loss(y_cv, y_prob_cv, eps=1e-15)
ac_nb_cv = accuracy_score(y_cv, y_pred_cv)
ll_nb_te = log_loss(y_test, y_prob, eps=1e-15)
ac_nb_te = accuracy_score(y_test, y_pred)


print("Log loss on Cross Validation Data using Naive Bayes",ll_nb_cv)
print("Log loss on Test Data using Naive Bayes",ll_nb_te)
print('Accuracy on Cross Validation using Naive Bayes', ac_nb_cv)
print('Accuracy on Test Data using Naive Bayes', ac_nb_te)

cnf_matrix(y_test, y_pred)
```

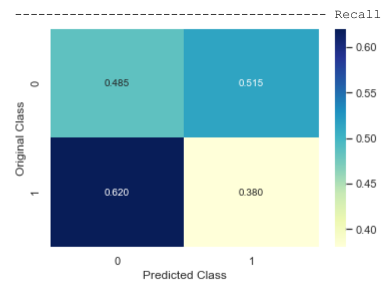
```
Log loss on Cross Validation Data using Naive Bayes 0.6304080630993817
Log loss on Test Data using Naive Bayes 0.5969289826648755
Accuracy on Cross Validation using Naive Bayes 0.5777233782129743
Accuracy on Test Data using Naive Bayes 0.6160626836434868
---------------------------------------- Confusion Matrix ----------------------------------------
```




```
---------------------------------------- Precision matrix (Columm Sum=1) ----------------------------------------
```




```
---------------------------------------- Recall matrix (Row sum=1) ----------------------------------------
```



Random Forest using Sklearn

Hyperparameter Tuning

In [77]:
```python
# Maximum number of levels in tree
n_estimators = [int(x) for x in np.linspace(start = 200, stop = 2000, num = 10)]

# Number of features to consider at every split
max_features = ['auto', 'log2', None]

# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(10, 110, num = 11)]

# Minimum number of samples required to split a node
min_samples_split = [2, 5, 10, 15]

# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 2, 3, 4, 5]

# Method of selecting samples for training each tree
bootstrap = [True, False]

# Create the random grid
params = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap}
clf4 = rgb(n_jobs=-1, random_state=42)
r_search = RandomizedSearchCV(clf4, param_distributions=params, return_train_score=True, random_state=42)
r_search.fit(x_tr, y_train)
```

Out[77]:
```
RandomizedSearchCV(estimator=RandomForestClassifier(n_jobs=-1, random_state=42),
                   param_distributions={'bootstrap': [True, False],
                                        'max_depth': [10, 20, 30, 40, 50, 60,
                                                      70, 80, 90, 100, 110],
                                        'max_features': ['auto', 'log2', None],
                                        'min_samples_leaf': [1, 2, 3, 4, 5],
                                        'min_samples_split': [2, 5, 10, 15],
                                        'n_estimators': [200, 400, 600, 800,
                                                         1000, 1200, 1400, 1600,
                                                         1800, 2000]},
                   random_state=42, return_train_score=True)
```

In [78]:
```python
print(f'The best hyperparameter values are {r_search.best_params_} at which the score is {r_search.best_scor
```

```
The best hyperparameter values are {'n_estimators': 1400, 'min_samples_split': 10, 'min_samples_leaf': 1, 'm
ax_features': 'log2', 'max_depth': 80, 'bootstrap': True} at which the score is 0.9890604103235352
```

Training the model

In [79]:
```python
clf4 = rgb(**r_search.best_params_, n_jobs=-1, random_state=42)
clf4.fit(x_tr, y_train)
cal_clf4 = CalibratedClassifierCV(clf4, cv='prefit')
cal_clf4.fit(x_tr, y_train)
```

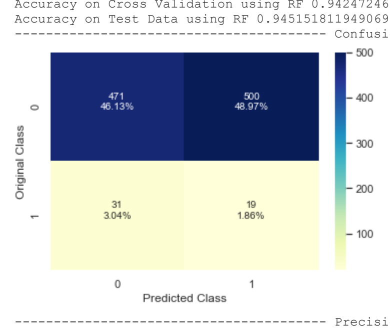
Out[79]:
```
CalibratedClassifierCV(base_estimator=RandomForestClassifier(max_depth=80,
                                                             max_features='log2',
                                                             min_samples_split=10,
                                                             n_estimators=1400,
                                                             n_jobs=-1,
                                                             random_state=42),
                       cv='prefit')
```

In [80]:
```python
y_pred_cv = cal_clf4.predict(x_cv)
y_prob_cv = cal_clf4.predict_proba(x_cv)
y_pred = cal_clf4.predict(x_te)
y_prob = cal_clf4.predict_proba(x_te)
```

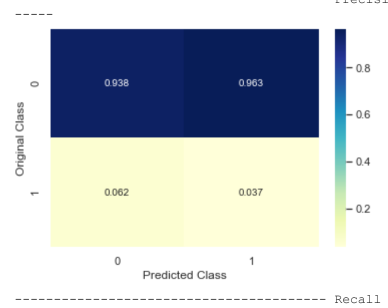
Performance of the model

In [81]:
```python
ll_rf_cv = log_loss(y_cv, y_prob_cv, eps=1e-15)
ac_rf_cv = accuracy_score(y_cv, y_pred_cv)
ll_rf_te = log_loss(y_test, y_prob, eps=1e-15)
ac_rf_te = accuracy_score(y_test, y_pred)


print("Log loss on Cross Validation Data using RF",ll_rf_cv)
print("Log loss on Test Data using RF",ll_rf_te)
print('Accuracy on Cross Validation using RF', ac_rf_cv)
print('Accuracy on Test Data using RF', ac_rf_te)

cnf_matrix(y_test, y_pred)
```

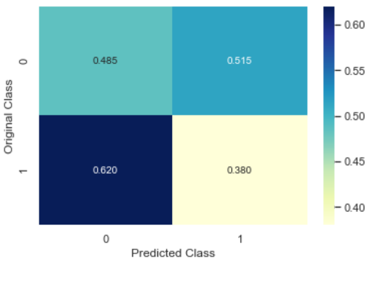
```
Log loss on Cross Validation Data using RF 0.3348050164010808
Log loss on Test Data using RF 0.3399874011973987
Accuracy on Cross Validation using RF 0.9424724602203183
Accuracy on Test Data using RF 0.9451518119490695
---------------------------------------- Confusion Matrix ----------------------------------------
```




```
---------------------------------------- Precision matrix (Columm Sum=1) ----------------------------------------
```



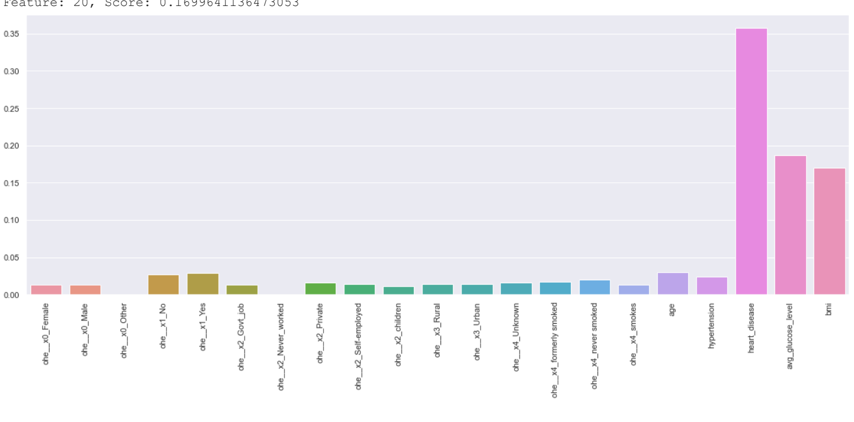

```
---------------------------------------- Recall matrix (Row sum=1) ----------------------------------------
```



Feature Importance

In [82]:
```
importance = clf4.feature_importances_
# summarize feature importance
for i,v in enumerate(importance):
    print(f'Feature: {i}, Score: {v}')

plt.figure(figsize=(20,7))
sns.barplot(x=[x for x in range(len(importance))], y=importance).set_xticklabels(features, rotation=90)
plt.show()
```

```
Feature: 0, Score: 0.012752798771207554
Feature: 1, Score: 0.013139025600361688
Feature: 2, Score: 2.616235320332209e-06
Feature: 3, Score: 0.02710540083742123
Feature: 4, Score: 0.02861370113588525
Feature: 5, Score: 0.013342904377548311
Feature: 6, Score: 4.943628701595869e-05
Feature: 7, Score: 0.016524918232487324
Feature: 8, Score: 0.014365108071047962
Feature: 9, Score: 0.011638684005633206
Feature: 10, Score: 0.013775553141228124
Feature: 11, Score: 0.013688283436881077
Feature: 12, Score: 0.016334701538669137
Feature: 13, Score: 0.01696287407025397
Feature: 14, Score: 0.019946127480100346
Feature: 15, Score: 0.0134679555440539
Feature: 16, Score: 0.029773739495578412
Feature: 17, Score: 0.023667986517847763
Feature: 18, Score: 0.35779219053178385
Feature: 19, Score: 0.1870918810423693
Feature: 20, Score: 0.1699641136473053
```



Random Forest using Xgboost

Hyperparameter Tuning

In [83]:
```
n_estimators = [int(x) for x in np.linspace(start = 100, stop = 2000, num = 10)]

learning_rate = [x for x in np.linspace(start=0.01, stop=0.2, num=10)]

min_child_weight = [1, 3, 5, 7]

max_depth = [3, 5, 7, 9]

subsample = [0.5, 0.6, 0.7, 0.8, 0.9, 1]

colsample_bytree = [0.5, 0.6, 0.7, 0.8, 0.9, 1]

# Create the random grid
params = {'n_estimators': n_estimators,
          'learning_rate':learning_rate,
          'min_child_weight': min_child_weight,
          'max_depth': max_depth,
          'subsample': subsample,
          'colsample_bytree': colsample_bytree}
clf5 = xgb(n_jobs=-1, random_state=42)
r_search = RandomizedSearchCV(clf5, param_distributions=params, return_train_score=True, random_state=42)
r_search.fit(x_tr, y_train)
```

```
[22:09:12] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:09:15] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:09:18] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:09:21] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:09:24] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:09:25] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:09:26] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:09:27] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:09:28] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:09:29] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:09:30] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:09:32] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:09:34] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:09:36] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:09:38] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:09:42] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:09:47] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:09:52] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:09:57] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:01] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:06] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:10] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:14] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:18] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:22] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:25] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:28] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:31] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:34] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:37] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:38] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:39] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:39] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:40] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:40] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:42] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:44] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:46] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:48] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:50] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:51] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:54] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:56] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:10:58] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:11:00] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:11:04] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:11:08] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:11:13] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:11:17] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:11:21] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[22:11:23] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

Out[83]:
```
RandomizedSearchCV(estimator=XGBRFClassifier(base_score=None, booster=None,
                                             colsample_bylevel=None,
                                             colsample_bytree=None, gamma=None,
                                             gpu_id=None,
                                             importance_type='gain',
                                             interaction_constraints=None,
                                             max_delta_step=None,
                                             max_depth=None,
                                             min_child_weight=None, missing=nan,
                                             monotone_constraints=None,
                                             n_estimators=100, n_jobs=-1,
                                             num_parallel_tree=None,
                                             objective='...
                                                           0.03111111111111111,
                                                           0.052222222222222225,
                                                           0.07333333333333333,
                                                           0.09444444444444444,
                                                           0.11555555555555555,
                                                           0.13666666666666667,
                                                           0.15777777777777778,
                                                           0.17888888888888889,
                                                           0.2],
                                        'max_depth': [3, 5, 7, 9],
                                        'min_child_weight': [1, 3, 5, 7],
                                        'n_estimators': [100, 311, 522, 733,
                                                         944, 1155, 1366, 1577,
                                                         1788, 2000],
                                        'subsample': [0.5, 0.6, 0.7, 0.8, 0.9,
                                                      1]},
                   random_state=42, return_train_score=True)
```

In [84]:
```
print(f'The best hyperparameter values are {r_search.best_params_} at which the score is {r_search.best_scor
```

```
The best hyperparameter values are {'subsample': 0.9, 'n_estimators': 100, 'min_child_weight': 1, 'max_dept
h': 9, 'learning_rate': 0.03111111111111111, 'colsample_bytree': 0.6} at which the score is 0.96283716141582
58
```

Training the model

In [85]:
```
clf5 = xgb(**r_search.best_params_, n_jobs=-1, random_state=42)
clf5.fit(x_tr, y_train)
cal_clf5 = CalibratedClassifierCV(clf5, cv='prefit')
cal_clf5.fit(x_tr, y_train)
```

```
[22:11:24] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starti
ng in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

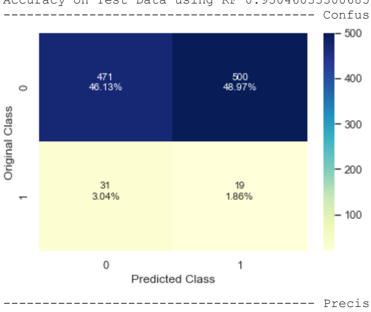
Out[85]:
```
CalibratedClassifierCV(base_estimator=XGBRFClassifier(base_score=0.5,
                                                      booster='gbtree',
                                                      colsample_bylevel=1,
                                                      colsample_bytree=0.6,
                                                      gamma=0, gpu_id=-1,
                                                      importance_type='gain',
                                                      interaction_constraints='',
                                                      learning_rate=0.03111111111111111,
                                                      max_delta_step=0,
                                                      max_depth=9,
                                                      min_child_weight=1,
                                                      missing=nan,
                                                      monotone_constraints='()',
                                                      n_estimators=100,
                                                      n_jobs=-1,
                                                      num_parallel_tree=100,
                                                      objective='binary:logistic',
                                                      random_state=42,
                                                      reg_alpha=0,
                                                      scale_pos_weight=1,
                                                      subsample=0.9,
                                                      tree_method='exact',
                                                      validate_parameters=1,
                                                      verbosity=None),
                       cv='prefit')
```

In [86]:
```
y_pred_cv = cal_clf5.predict(x_cv)
y_prob_cv = cal_clf5.predict_proba(x_cv)
y_pred = cal_clf5.predict(x_te)
y_prob = cal_clf5.predict_proba(x_te)
```

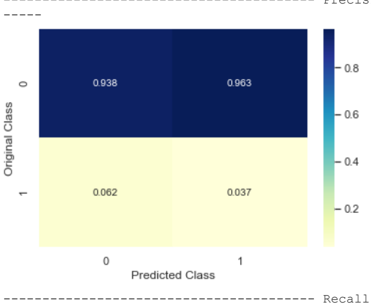
Performance of the model

In [87]:
```
ll_xg_cv = log_loss(y_cv, y_prob_cv, eps=1e-15)
ac_xg_cv = accuracy_score(y_cv, y_pred_cv)
ll_xg_te = log_loss(y_test, y_prob, eps=1e-15)
ac_xg_te = accuracy_score(y_test, y_pred)


print("Log loss on Cross Validation Data using RF",ll_xg_cv)
print("Log loss on Test Data using RF",ll_xg_te)
print('Accuracy on Cross Validation using RF', ac_xg_cv)
print('Accuracy on Test Data using RF', ac_xg_te)

cnf_matrix(y_test, y_pred)
```

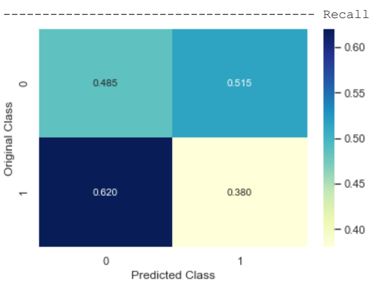
```
Log loss on Cross Validation Data using RF 0.5456568501282764
Log loss on Test Data using RF 0.6049738340084296
Accuracy on Cross Validation using RF 0.9363525091799265
Accuracy on Test Data using RF 0.930460333006856
---------------------------------------- Confusion Matrix ----------------------------------------
```




```
---------------------------------------- Precision matrix (Columm Sum=1) ----------------------------------------
```



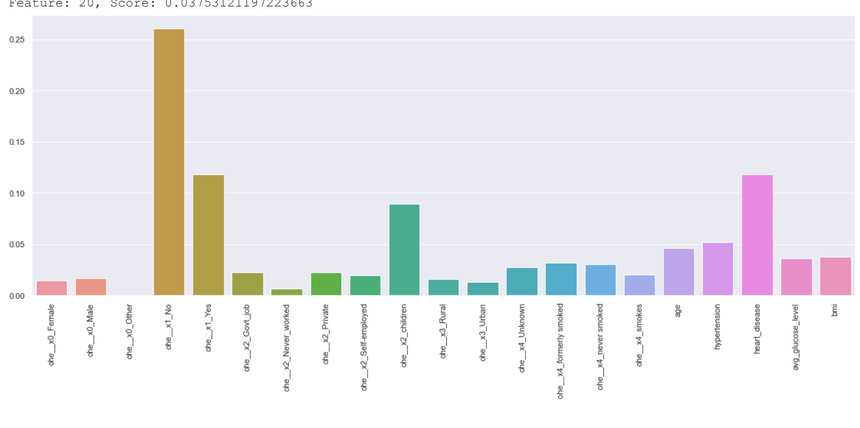

```
---------------------------------------- Recall matrix (Row sum=1) ----------------------------------------
```



Feature Importance

In [88]:
```
importance = clf5.feature_importances_
# summarize feature importance
for i,v in enumerate(importance):
    print(f'Feature: {i}, Score: {v}')

plt.figure(figsize=(20,7))
sns.barplot(x=[x for x in range(len(importance))], y=importance).set_xticklabels(features, rotation=90)
plt.show()
```

```
Feature: 0, Score: 0.014785390347242355
Feature: 1, Score: 0.016840120777487755
Feature: 2, Score: 0.0
Feature: 3, Score: 0.26061001420021057
Feature: 4, Score: 0.11831574887037277
Feature: 5, Score: 0.0228144321590662
Feature: 6, Score: 0.006446104031056166
Feature: 7, Score: 0.022581875324249268
Feature: 8, Score: 0.019605936482548714
Feature: 9, Score: 0.08927551656961441
Feature: 10, Score: 0.015692954882979393
Feature: 11, Score: 0.012989203445613384
Feature: 12, Score: 0.027522603049874306
Feature: 13, Score: 0.03213122859597206
Feature: 14, Score: 0.030077636241912842
Feature: 15, Score: 0.02024657279253006
Feature: 16, Score: 0.046271972358226776
Feature: 17, Score: 0.051927436143519866
Feature: 18, Score: 0.11803538352251053
Feature: 19, Score: 0.03629869595170021
Feature: 20, Score: 0.03753121197223663
```



Stacking Classifier

In [89]:
```
estimators = [('svc', clf2), ('nb', clf3), ('rf',  clf4)]

scl = StackingClassifier(estimators=estimators, final_estimator=clf1, n_jobs=-1)
scl.fit(x_tr, y_train)
cal_clf = CalibratedClassifierCV(scl, cv='prefit')
cal_clf.fit(x_tr, y_train)
```

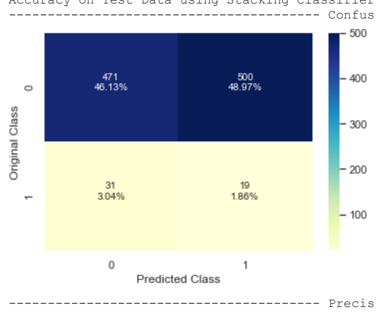
Out[89]:
```
CalibratedClassifierCV(base_estimator=StackingClassifier(estimators=[('svc',
                                                                      SGDClassifier(n_jobs=-1,
                                                                                    random_state=42)),
                                                                     ('nb',
                                                                      MultinomialNB(alpha=0.01)),
                                                                     ('rf',
                                                                      RandomForestClassifier(max_depth=80,
                                                                                             max_features='l
og2',
                                                                                             min_samples_spl
it=10,
                                                                                             n_estimators=14
00,
                                                                                             n_jobs=-1,
                                                                                             random_state=4
2))],
                                                         final_estimator=SGDClassifier(alpha=0.001,
                                                                                       loss='log',
                                                                                       n_jobs=-1,
                                                                                       random_state=42),
                                                         n_jobs=-1),
                       cv='prefit')
```

In [90]:
```
y_pred_cv = cal_clf.predict(x_cv)
y_prob_cv = cal_clf.predict_proba(x_cv)
y_pred = cal_clf.predict(x_te)
y_prob = cal_clf.predict_proba(x_te)
```

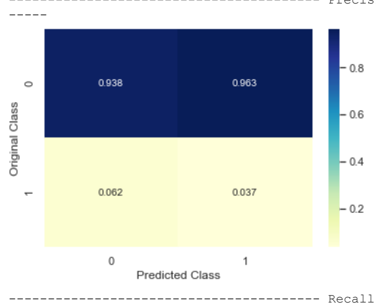
Performance of the model

In [91]:
```
ll_sc_cv = log_loss(y_cv, y_prob_cv, eps=1e-15)
ac_sc_cv = accuracy_score(y_cv, y_pred_cv)
ll_sc_te = log_loss(y_test, y_prob, eps=1e-15)
ac_sc_te = accuracy_score(y_test, y_pred)


print("Log loss on Cross Validation Data using Stacking Classifier",ll_sc_cv)
print("Log loss on Test Data using Stacking Classifier",ll_sc_te)
print('Accuracy on Cross Validation using Stacking Classifier', ac_sc_cv)
print('Accuracy on Test Data using Stacking Classifier', ac_sc_te)

cnf_matrix(y_test, y_pred)
```

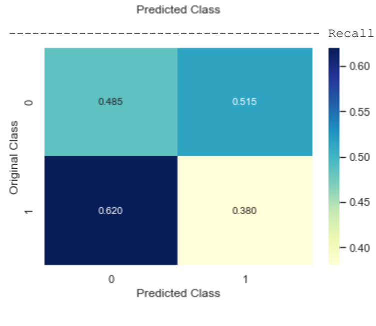
```
Log loss on Cross Validation Data using Stacking Classifier 0.3339721346074445
Log loss on Test Data using Stacking Classifier 0.3394177727229881
Accuracy on Cross Validation using Stacking Classifier 0.9424724602203183
Accuracy on Test Data using Stacking Classifier 0.9451518119490695
---------------------------------------- Confusion Matrix ----------------------------------------
```




```
---------------------------------------- Precision matrix (Columm Sum=1) ----------------------------------------
```




```
---------------------------------------- Recall matrix (Row sum=1) ----------------------------------------
```



Summary of Performance

In [92]:
```
table = PrettyTable()
table.field_names = ['Model', 'CV Log Loss', 'Test Log Loss', 'CV Accuracy', 'Test Accuracy']
table.add_rows([['Random Model', round(ll_rm_cv,3), round(ll_rm_te,4), round(ac_rm_cv,3), round(ac_rm_te,3)]
               ['Logistic Regression', round(ll_lg_cv,3), round(ll_lg_te,3), round(ac_lg_cv,3), round(ac_lg
               ['Naive Bayes', round(ll_nb_cv,3), round(ll_nb_te,3), round(ac_nb_cv,3), round(ac_nb_te,3)],
               ['SVM', round(ll_svm_cv,3), round(ll_svm_te,3), round(ac_svm_cv,3), round(ac_svm_te,3)],
               ['Random Forest(Scikit)', round(ll_rf_cv,3), round(ll_rf_te,3), round(ac_rf_cv,3), round(ac_
               ['Random Forest(Xgboost)', round(ll_xg_cv,3), round(ll_xg_te,3), round(ac_xg_cv,3), round(ac
               ['Stacking Classifier', round(ll_sc_cv,3), round(ll_sc_te,3), round(ac_sc_cv,3), round(ac_sc
```

In [93]:
```
table.set_style(DEFAULT)
print(table)
```

Model	CV Log Loss	Test Log Loss	CV Accuracy	Test Accuracy
Random Model	0.926	0.9333	0.461	0.48
Logistic Regression	0.513	0.523	0.749	0.733
Naive Bayes	0.63	0.597	0.578	0.616
SVM	0.518	0.536	0.743	0.737
Random Forest (Scikit)	0.335	0.34	0.942	0.945
Random Forest(Xgboost)	0.546	0.605	0.936	0.93
Stacking Classifier	0.334	0.339	0.942	0.945

So our best model is Random Forest using sklearn with **an accuracy of 94.5% and log loss of 0.339**