TP1_Stroke_Prediction_Charbel_Abi_Hana

March 25, 2022

0.1 Importing Relevant Libraries

[1]:
```
import pandas as pd
import numpy as np
import sklearn

# data preprocessing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, MinMaxScaler
# metrics
from sklearn.metrics import (confusion_matrix, precision_score,
                             recall_score, accuracy_score,
                             f1_score, mean_squared_error, roc_curve, auc,␣
 ↪balanced_accuracy_score)
from sklearn.metrics import PrecisionRecallDisplay, ConfusionMatrixDisplay,␣
 ↪RocCurveDisplay, classification_report

# model selection
from sklearn.model_selection import GridSearchCV, StratifiedKFold

# classification models
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier

# oversampling
from imblearn.over_sampling import RandomOverSampler, ADASYN, SMOTE

# neural network
from sklearn.neural_network import MLPClassifier
# visualization
import seaborn as sns
import matplotlib.pyplot as plt

from matplotlib.patches import Rectangle
from matplotlib.patches import Patch
from matplotlib.lines import Line2D
```

0.2 Data Analysis

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

[2]:
```
         id  gender   age  hypertension  heart_disease ever_married  \
0      9046    Male  67.0             0              1          Yes
1     51676  Female  61.0             0              0          Yes
2     31112    Male  80.0             0              1          Yes
3     60182  Female  49.0             0              0          Yes
4      1665  Female  79.0             1              0          Yes
…       …     …   …           …             …          …
5105  18234  Female  80.0             1              0          Yes
5106  44873  Female  81.0             0              0          Yes
5107  19723  Female  35.0             0              0          Yes
5108  37544    Male  51.0             0              0          Yes
5109  44679  Female  44.0             0              0          Yes

          work_type Residence_type  avg_glucose_level   bmi   smoking_status  \
0           Private          Urban             228.69  36.6  formerly smoked
1     Self-employed          Rural             202.21   NaN     never smoked
2           Private          Rural             105.92  32.5     never smoked
3           Private          Urban             171.23  34.4           smokes
4     Self-employed          Rural             174.12  24.0     never smoked
…               …            …                 …   …              …
5105        Private          Urban              83.75   NaN     never smoked
5106  Self-employed          Urban             125.20  40.0     never smoked
5107  Self-employed          Rural              82.99  30.6     never smoked
5108        Private          Rural             166.29  25.6  formerly smoked
5109       Govt_job          Urban              85.28  26.2          Unknown

      stroke
0          1
1          1
2          1
3          1
4          1
…        …
5105       0
5106       0
5107       0
5108       0
5109       0

[5110 rows x 12 columns]
```

[3]:
```python
# data shape
rows, cols = dataframe.shape
print(f"The dataset is composed of {rows} rows and {cols} columns.")
```

```
The dataset is composed of 5110 rows and 12 columns.
```

[4]:
```python
dataframe.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
```

We observe multiple NaN values for the *<bmi>* category (exactly 201 values) which make up approximately **4%** of the data for this feature. We can look into replacing the NaN values with the mean for this category. We also drop the **id** comlumn from our dataset as it has no influence on our expected outcome.

[5]:
```python
dataframe = dataframe.drop(labels= "id", axis=1)
dataframe.head()
```

[5]:

	gender	age	hypertension	heart_disease	ever_married	work_type
0	Male	67.0	0	1	Yes	Private
1	Female	61.0	0	0	Yes	Self-employed
2	Male	80.0	0	1	Yes	Private
3	Female	49.0	0	0	Yes	Private
4	Female	79.0	1	0	Yes	Self-employed

	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	Urban	228.69	36.6	formerly smoked	1
1	Rural	202.21	NaN	never smoked	1
2	Rural	105.92	32.5	never smoked	1
3	Urban	171.23	34.4	smokes	1
4	Rural	174.12	24.0	never smoked	1

0.2.1 Some Statistics For the Numerical Data

[6]:
```
dataframe.describe()
```

[6]:
```
               age  hypertension  heart_disease  avg_glucose_level  \
count  5110.000000   5110.000000    5110.000000        5110.000000
mean     43.226614      0.097456       0.054012         106.147677
std      22.612647      0.296607       0.226063          45.283560
min       0.080000      0.000000       0.000000          55.120000
25%      25.000000      0.000000       0.000000          77.245000
50%      45.000000      0.000000       0.000000          91.885000
75%      61.000000      0.000000       0.000000         114.090000
max      82.000000      1.000000       1.000000         271.740000

               bmi       stroke
count  4909.000000  5110.000000
mean     28.893237     0.048728
std       7.854067     0.215320
min      10.300000     0.000000
25%      23.500000     0.000000
50%      28.100000     0.000000
75%      33.100000     0.000000
max      97.600000     1.000000
```

0.2.2 Representing Unique Values of Categorical Features

[7]:
```
# get categorical data having multiple labels
categorical = ["gender", "hypertension", "heart_disease", "ever_married",␣
↪"work_type", "Residence_type", "smoking_status"]
categorical_df = pd.DataFrame()
for categorical_feature in categorical:
    tmp_df = pd.DataFrame({categorical_feature:dataframe[categorical_feature].
↪unique()})
    categorical_df = pd.concat([categorical_df, tmp_df], axis=1)
categorical_df.head()
```

[7]:
```
   gender  hypertension  heart_disease ever_married      work_type  \
0    Male           0.0            1.0          Yes        Private
1  Female           1.0            0.0           No  Self-employed
2   Other           NaN            NaN          NaN       Govt_job
3     NaN           NaN            NaN          NaN       children
4     NaN           NaN            NaN          NaN   Never_worked

  Residence_type   smoking_status
0          Urban  formerly smoked
1          Rural     never smoked
2            NaN           smokes
3            NaN          Unknown
```

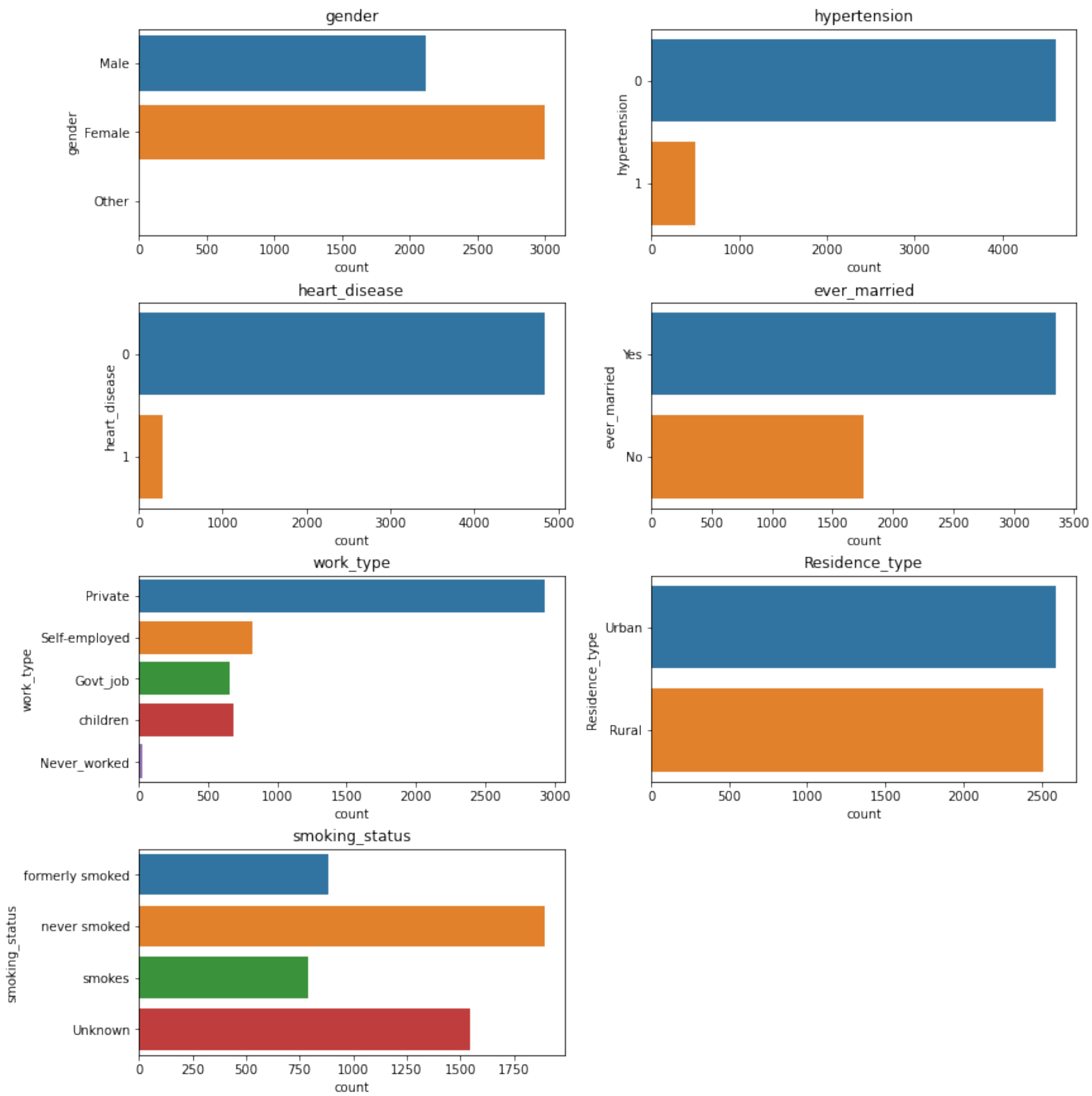
```
4            NaN               NaN
```

0.2.3 Visualizing Distribution of Categorical Features

[8]:
```
X = dataframe.drop(labels=["stroke"], axis=1)
Y = dataframe["stroke"]

X.head()
```

[8]:
```
   gender   age  hypertension  heart_disease ever_married      work_type  \
0    Male  67.0             0              1          Yes        Private
1  Female  61.0             0              0          Yes  Self-employed
2    Male  80.0             0              1          Yes        Private
3  Female  49.0             0              0          Yes        Private
4  Female  79.0             1              0          Yes  Self-employed

  Residence_type  avg_glucose_level   bmi   smoking_status
0          Urban             228.69  36.6  formerly smoked
1          Rural             202.21   NaN     never smoked
2          Rural             105.92  32.5     never smoked
3          Urban             171.23  34.4           smokes
4          Rural             174.12  24.0     never smoked
```

[9]:
```
all_categories = categorical

fig, ax = plt.subplots(4, 2, figsize=(12,5), constrained_layout=True)
fig.delaxes(ax[3,1])
fig.set_figheight(12)
for i, cat_var in enumerate(all_categories):
    try:
        j,k = np.unravel_index(i, shape= (4, 2))
        cp = sns.countplot(y=cat_var, data=X, label='features', ax=ax[j,k])
        ax[j,k].set_title(cat_var)
    except Exception as e:
        print(e)
plt.show()
```



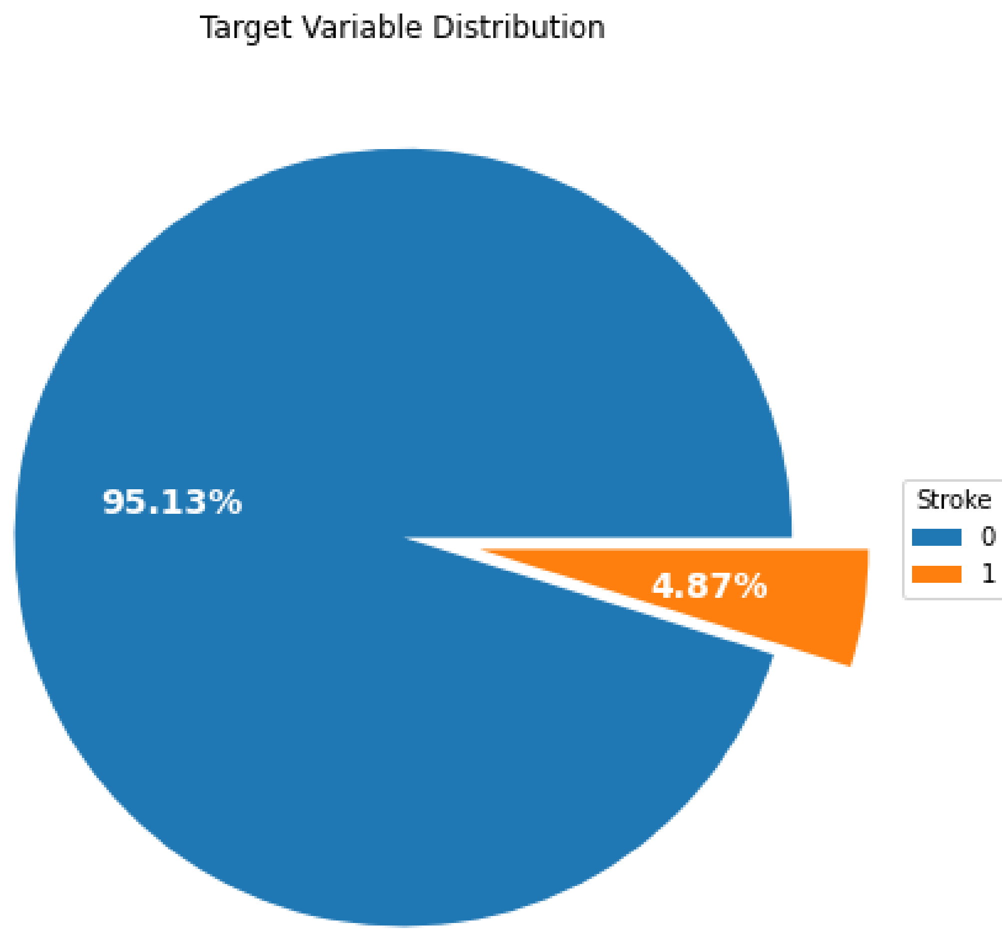
0.2.4 Visualizing Distribution of Target

Helper Function - Target Distribution Visualizer

[10]:
```python
def vis_target_dist(target_var, title):

    pie_data = target_var.value_counts(normalize=True).values * 100
    pie_label = target_var.value_counts(normalize=True).index

    fig, ax = plt.subplots(figsize=(8,6))

    wedges, texts, autotexts = ax.pie(pie_data, startangle=0, explode=[0, 0.2],
                                      autopct='%.2f%%', textprops={'color':'w',␣
↪'fontsize':14, 'weight':'bold'})
```

```
    ax.legend(wedges, pie_label,
              title='Stroke',
              loc='center left', bbox_to_anchor=(1, 0.5))

    plt.title(title)
    plt.tight_layout()
```

[11]:
```
vis_target_dist(Y, "Target Variable Distribution")
plt.show()
```



0.2.5 Finding Correlation of the Categorical Features

In this part, we want to represent the correlation between each of the features in the dataset against the target value *stroke*. Pearson's correleation (source) can be easily obtained using the `pandas` library. This approach allows us to recognize the most relevant features in our dataset by identifying the ones with the lowest correlation value calculated by Pearson's correlation.

[12]:
```python
# get a one-hot-encoded representation of the categorical data (required for
↪the Pearson Correlation calculation)
dataframe_ohe = pd.get_dummies(data=dataframe)
dataframe_ohe
```

[12]:
```
       age  hypertension  heart_disease  avg_glucose_level   bmi  stroke  \
0     67.0             0              1             228.69  36.6       1
1     61.0             0              0             202.21   NaN       1
2     80.0             0              1             105.92  32.5       1
3     49.0             0              0             171.23  34.4       1
4     79.0             1              0             174.12  24.0       1
…      …            …              …                 …     …       …
5105  80.0             1              0              83.75   NaN       0
5106  81.0             0              0             125.20  40.0       0
5107  35.0             0              0              82.99  30.6       0
5108  51.0             0              0             166.29  25.6       0
5109  44.0             0              0              85.28  26.2       0

      gender_Female  gender_Male  gender_Other  ever_married_No  …  \
0                 0            1             0                0  …
1                 1            0             0                0  …
2                 0            1             0                0  …
3                 1            0             0                0  …
4                 1            0             0                0  …
…               …            …             …               …  …
5105              1            0             0                0  …
5106              1            0             0                0  …
5107              1            0             0                0  …
5108              0            1             0                0  …
5109              1            0             0                0  …

      work_type_Never_worked  work_type_Private  work_type_Self-employed  \
0                          0                  1                        0
1                          0                  0                        1
2                          0                  1                        0
3                          0                  1                        0
4                          0                  0                        1
…                        …                  …                        …
5105                       0                  1                        0
5106                       0                  0                        1
5107                       0                  0                        1
5108                       0                  1                        0
5109                       0                  0                        0
```

```
      work_type_children  Residence_type_Rural  Residence_type_Urban  \
0                      0                     0                     1
1                      0                     1                     0
2                      0                     1                     0
3                      0                     0                     1
4                      0                     1                     0
…                    …                   …                   …
5105                   0                     0                     1
5106                   0                     0                     1
5107                   0                     1                     0
5108                   0                     1                     0
5109                   0                     0                     1

      smoking_status_Unknown  smoking_status_formerly smoked  \
0                          0                               1
1                          0                               0
2                          0                               0
3                          0                               0
4                          0                               0
…                        …                             …
5105                       0                               0
5106                       0                               0
5107                       0                               0
5108                       0                               1
5109                       1                               0

      smoking_status_never smoked  smoking_status_smokes
0                               0                      0
1                               1                      0
2                               1                      0
3                               0                      1
4                               1                      0
…                             …                    …
5105                            1                      0
5106                            1                      0
5107                            1                      0
5108                            0                      0
5109                            0                      0

[5110 rows x 22 columns]
```

[13]:
```python
# setting a figure size for the heatmap
plt.figure(figsize=(16,12))
# calculating correlation and storing it in a dataframe
cor = dataframe_ohe.corr()
cor.head()
```

[13]:

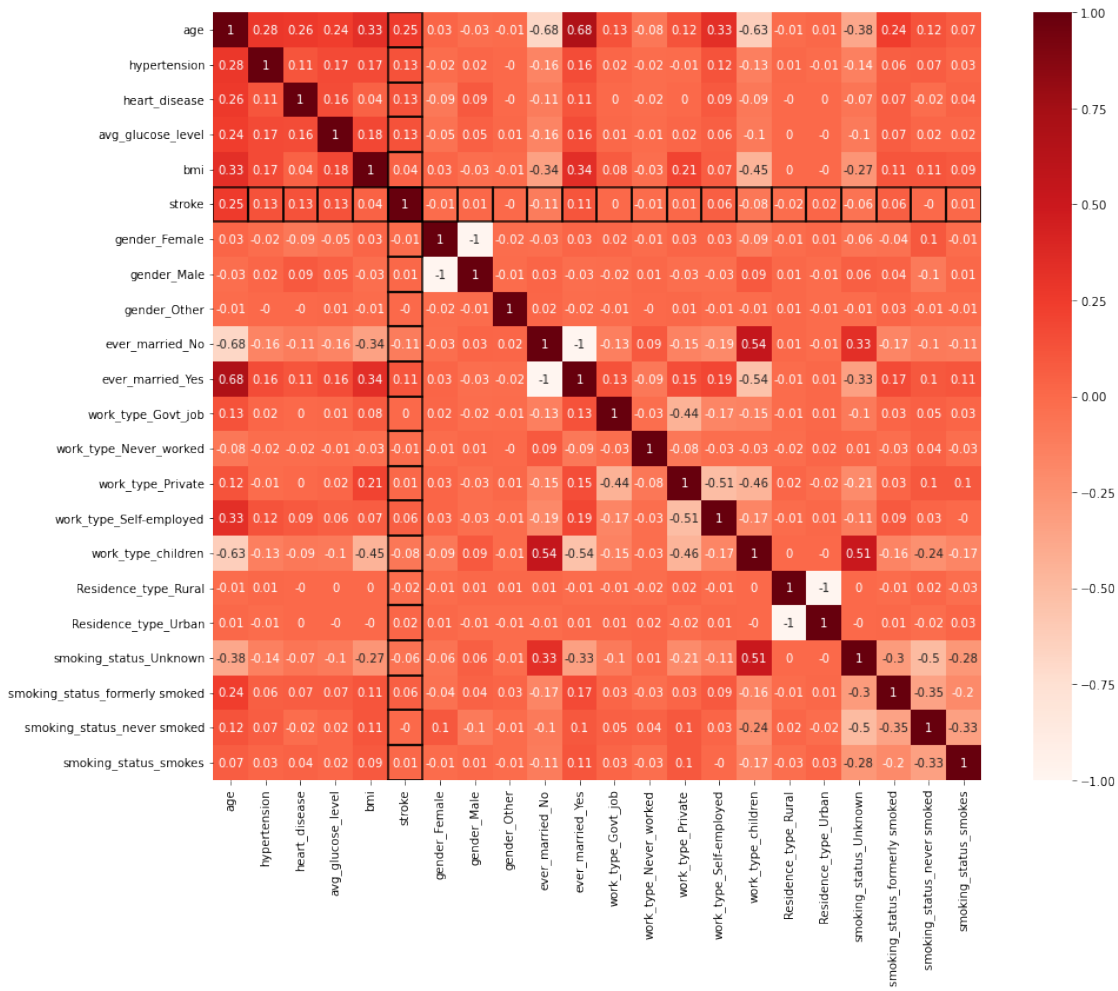
```
                        age  hypertension  heart_disease  avg_glucose_level  \
age                1.000000      0.276398       0.263796           0.238171
hypertension       0.276398      1.000000       0.108306           0.174474
heart_disease      0.263796      0.108306       1.000000           0.161857
avg_glucose_level  0.238171      0.174474       0.161857           1.000000
bmi                0.333398      0.167811       0.041357           0.175502

                        bmi    stroke  gender_Female  gender_Male  \
age                0.333398  0.245257       0.027924    -0.027623
hypertension       0.167811  0.127904      -0.021143     0.021275
heart_disease      0.041357  0.134914      -0.085617     0.085717
avg_glucose_level  0.175502  0.131945      -0.054902     0.054580
bmi                1.000000  0.042374       0.026360    -0.026020

                   gender_Other  ever_married_No  …  work_type_Never_worked  \
age                   -0.010659        -0.679125  …               -0.078653
hypertension          -0.004597        -0.164243  …               -0.021608
heart_disease         -0.003343        -0.114644  …               -0.015712
avg_glucose_level      0.011489        -0.155068  …               -0.014675
bmi                   -0.011802        -0.341695  …               -0.028602

                   work_type_Private  work_type_Self-employed  \
age                         0.116534                 0.327989
hypertension               -0.005413                 0.115442
heart_disease               0.000027                 0.086760
avg_glucose_level           0.016588                 0.062694
bmi                         0.208029                 0.072701

                   work_type_children  Residence_type_Rural  \
age                         -0.634215             -0.014180
hypertension                -0.129506              0.007913
heart_disease               -0.091634             -0.003092
avg_glucose_level           -0.102250              0.004946
bmi                         -0.448674              0.000122

                   Residence_type_Urban  smoking_status_Unknown  \
age                            0.014180               -0.378231
hypertension                  -0.007913               -0.141501
heart_disease                  0.003092               -0.066731
avg_glucose_level             -0.004946               -0.095131
bmi                           -0.000122               -0.270340

                   smoking_status_formerly smoked  \
age                                      0.236897
hypertension                             0.058853
heart_disease                            0.066804
avg_glucose_level                        0.068111
```

```
bmi                                           0.107031

                   smoking_status_never smoked  smoking_status_smokes
age                                   0.119307               0.073133
hypertension                          0.065063               0.031240
heart_disease                        -0.021856               0.044049
avg_glucose_level                     0.023885               0.017646
bmi                                   0.107964               0.088324

[5 rows x 22 columns]
```

```
<Figure size 1152x864 with 0 Axes>
```

[14]:

```
plt.figure(figsize=(16,12))
ax = sns.heatmap(cor.round(2), square=True, cmap=plt.cm.Reds, annot=True)
for i in dataframe_ohe.index[dataframe_ohe['stroke'] == True].tolist():
    j = dataframe_ohe.columns.get_loc('stroke')
    ax.add_patch(Rectangle((i, j), 1, 1, ec='black', fc='none', lw=2, alpha=0.
 ↪7))
    ax.add_patch(Rectangle((j, i), 1, 1, ec='black', fc='none', lw=2, alpha=0.
 ↪7))
plt.show()
```



```
[15]: #Correlation with output variable
      cor_target = abs(cor["stroke"])
      #Selecting highly correlated features
      cor_target
```

```
[15]: age                          0.245257
      hypertension                 0.127904
      heart_disease                0.134914
      avg_glucose_level            0.131945
      bmi                          0.042374
      stroke                       1.000000
      gender_Female                0.009027
      gender_Male                  0.009117
      gender_Other                 0.003166
      ever_married_No              0.108340
      ever_married_Yes             0.108340
```

```
work_type_Govt_job                0.002677
work_type_Never_worked            0.014882
work_type_Private                 0.011888
work_type_Self-employed           0.062168
work_type_children                0.083869
Residence_type_Rural              0.015458
Residence_type_Urban              0.015458
smoking_status_Unknown            0.055892
smoking_status_formerly smoked    0.064556
smoking_status_never smoked       0.004129
smoking_status_smokes             0.008939
Name: stroke, dtype: float64
```

From the correlation values calculated, for each output in a categorical feature, if one output isn't highly correlated to the target **stroke**, we can deduce that the entire feature is relevant and not correlated. All of the features in our dataset are relevant. We note the 3 most relevant based on correlation values: - **gender** - **work_type** - **smoking_status/Residence_type**

0.2.6 Inspecting Missing or NaN Values

[16]:
```python
def summarize_missingness(df):
    '''
    Utility function to summarize missing or NaN values
    '''
    nulls = df.isnull()
    counts = nulls.sum()
    percs = nulls.mean().mul(100.)

    nulls_df = pd.DataFrame({'Count of missing/NaN values': counts, 'Percentage␣
 ↪of missing values': percs},
                            index=counts.index)

    display(nulls_df)
```

[17]:
```python
vars_with_na = [col for col in dataframe_ohe if dataframe_ohe[col].isnull().
 ↪sum() > 0]
summarize_missingness(dataframe[vars_with_na])
```

```
     Count of missing/NaN values  Percentage of missing values
bmi                          201                      3.933464
```

We can see that only the feature **bmi** has 201 missing or NaN values which represent ~4% of the datapoints.

0.2.7 Some More EDA

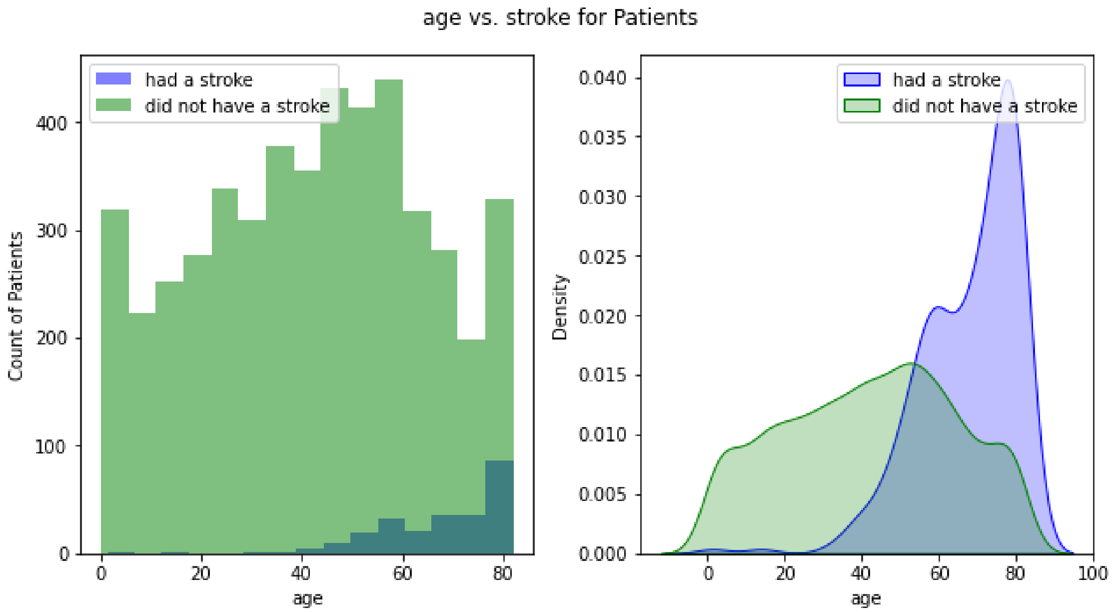
In this part, we inspect the features of the dataset in function of the target class **stroke**. We seek to further understand the underlying relation between the dataset features and the output obtained.

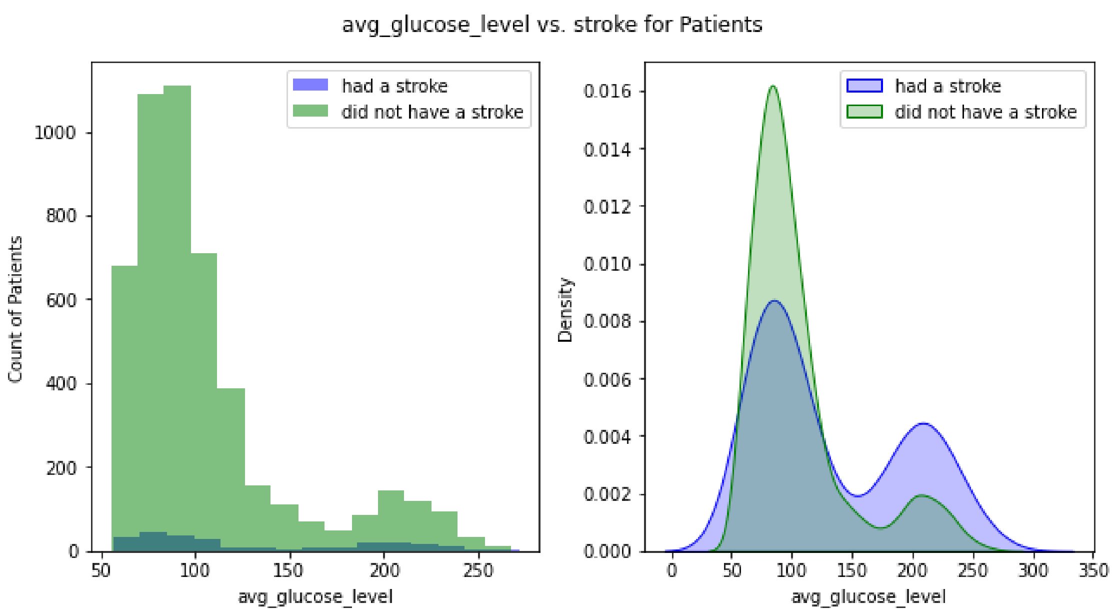
Numerical Variables Vs Stroke The numerical variables in our dataset are **age**, **bmi** and **avg_glucose_level**. In this part, we will try to comprehend the effect of each of these variables on our target.

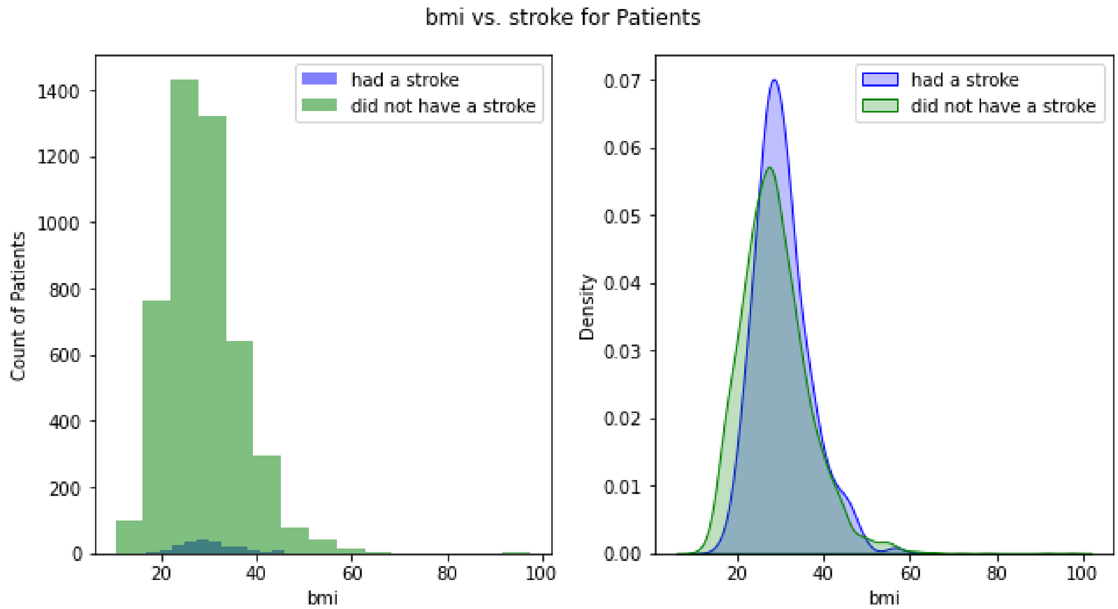
[18]:
```
num_vars = dataframe.select_dtypes(include=['float']).columns.tolist()
num_vars
```

[18]:
```
['age', 'avg_glucose_level', 'bmi']
```

[19]:
```
target_var = "stroke"
color1, color2 = "blue", "green"
for num_var in num_vars:
    fig, ax = plt.subplots(nrows= 1, ncols= 2 )
    fig.set_figheight(5)
    fig.set_figwidth(9)

    ax[0].hist(dataframe[dataframe[target_var]==1][f"{num_var}"], bins=15,␣
 ↪alpha=0.5, color=color1, label="had a stroke")
    ax[0].hist(dataframe[dataframe[target_var]==0][f"{num_var}"], bins=15,␣
 ↪alpha=0.5, color=color2, label="did not have a stroke")

    ax[0].set_xlabel(num_var)
    ax[0].set_ylabel("Count of Patients")
    ax[0].legend();


    sns.kdeplot(dataframe[dataframe[target_var]==1][num_var], shade=True,␣
 ↪color=color1, label="had a stroke", ax=ax[1])
    sns.kdeplot(dataframe[dataframe[target_var]==0][num_var], shade=True,␣
 ↪color=color2, label="did not have a stroke", ax=ax[1])

    ax[1].set_xlabel(num_var)
    ax[1].set_ylabel("Density")
    ax[1].legend();
    fig.suptitle(f"{num_var} vs. {target_var} for Patients");
    plt.tight_layout()
    plt.show()
```


age vs. stroke for Patients
had a stroke
did not have a stroke
Count of Patients
Density
age


avg_glucose_level vs. stroke for Patients
had a stroke
did not have a stroke
Count of Patients
Density
avg_glucose_level



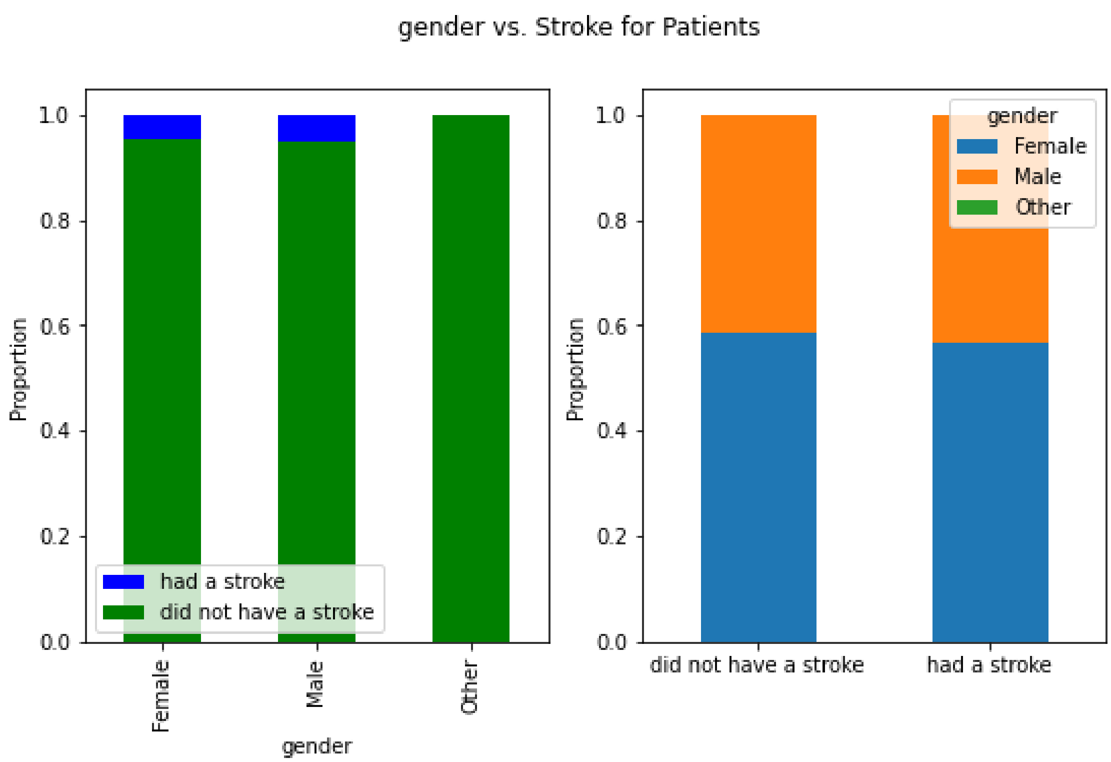
Categorical Variables Vs Stroke

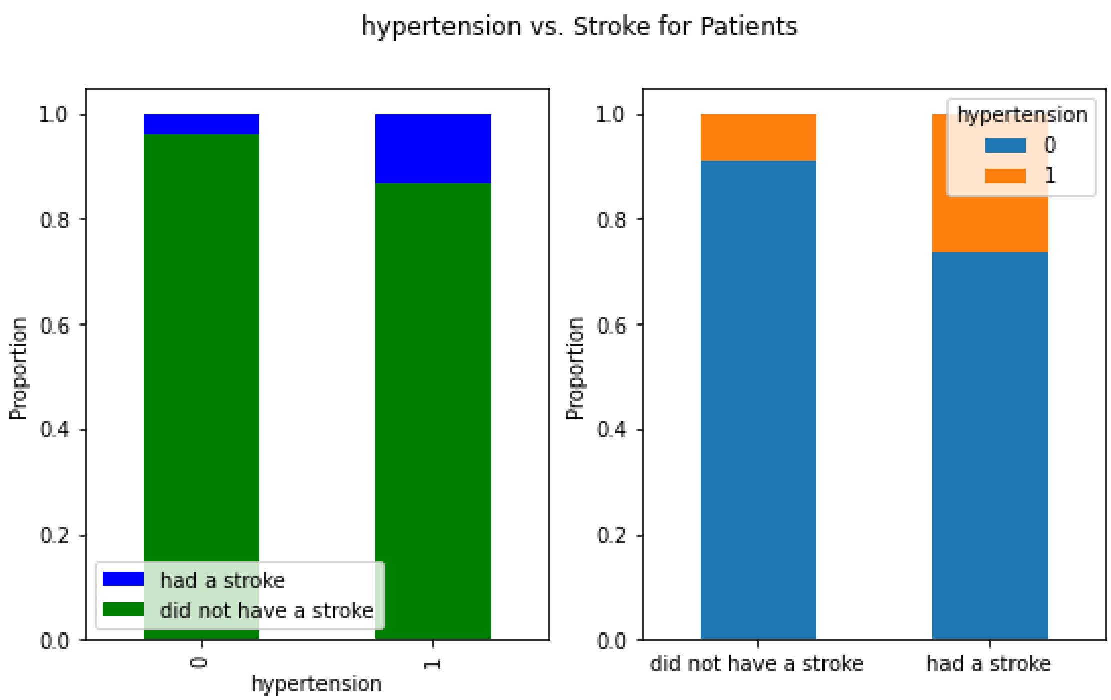
[20]:
```
cat_vars = categorical
cat_vars
```

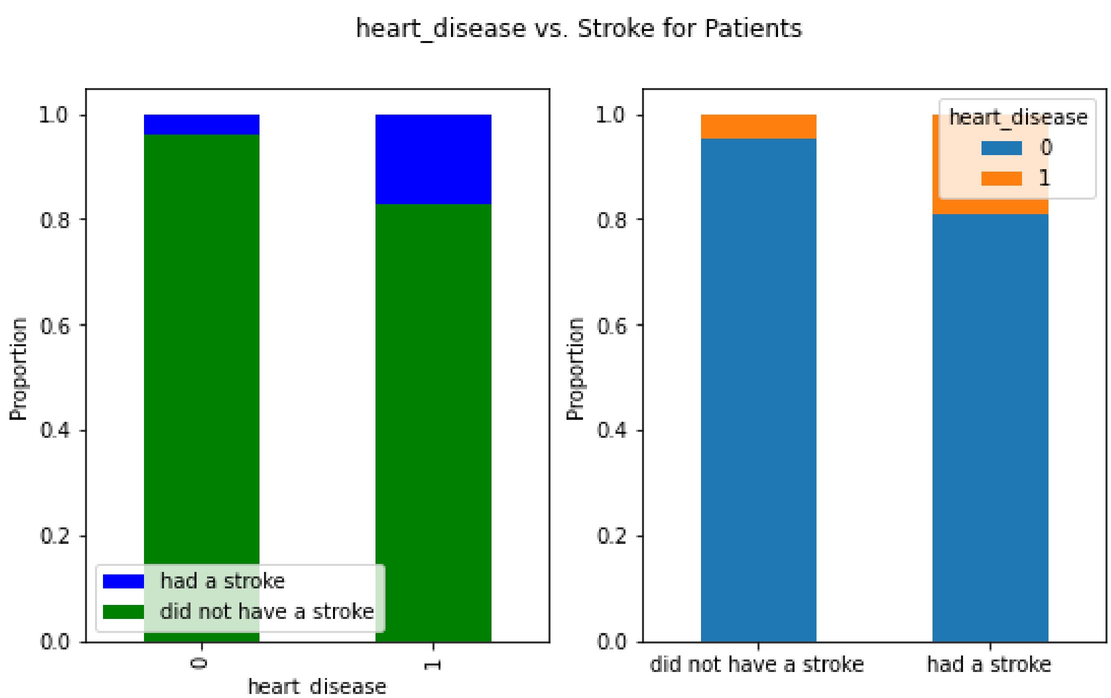
[20]:
```
['gender',
 'hypertension',
 'heart_disease',
 'ever_married',
 'work_type',
 'Residence_type',
 'smoking_status']
```

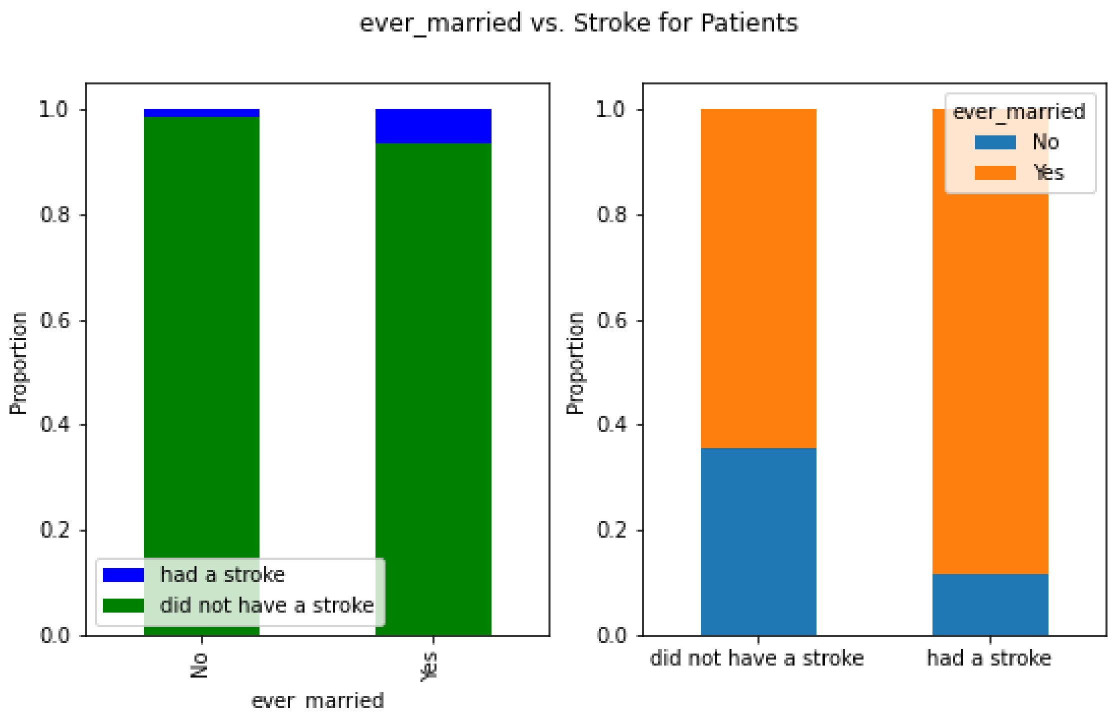
[21]:
```
target_var = "stroke"
for cat_var in cat_vars:
    tmp_counts_df = dataframe.groupby([cat_var, target_var])["age"].count().
 ↪unstack()

    tmp_target_perc_df = tmp_counts_df.T.div(tmp_counts_df.T.sum()).T
    tmp_feature_perc_df = tmp_counts_df.div(tmp_counts_df.sum()).T

    fig, ax = plt.subplots(nrows=1, ncols= 2)
    fig.set_figheight(5)
    fig.set_figwidth(9)

    tmp_target_perc_df.plot(kind="bar", stacked=True, color=["green", "blue"],␣
 ↪ax=ax[0])
```

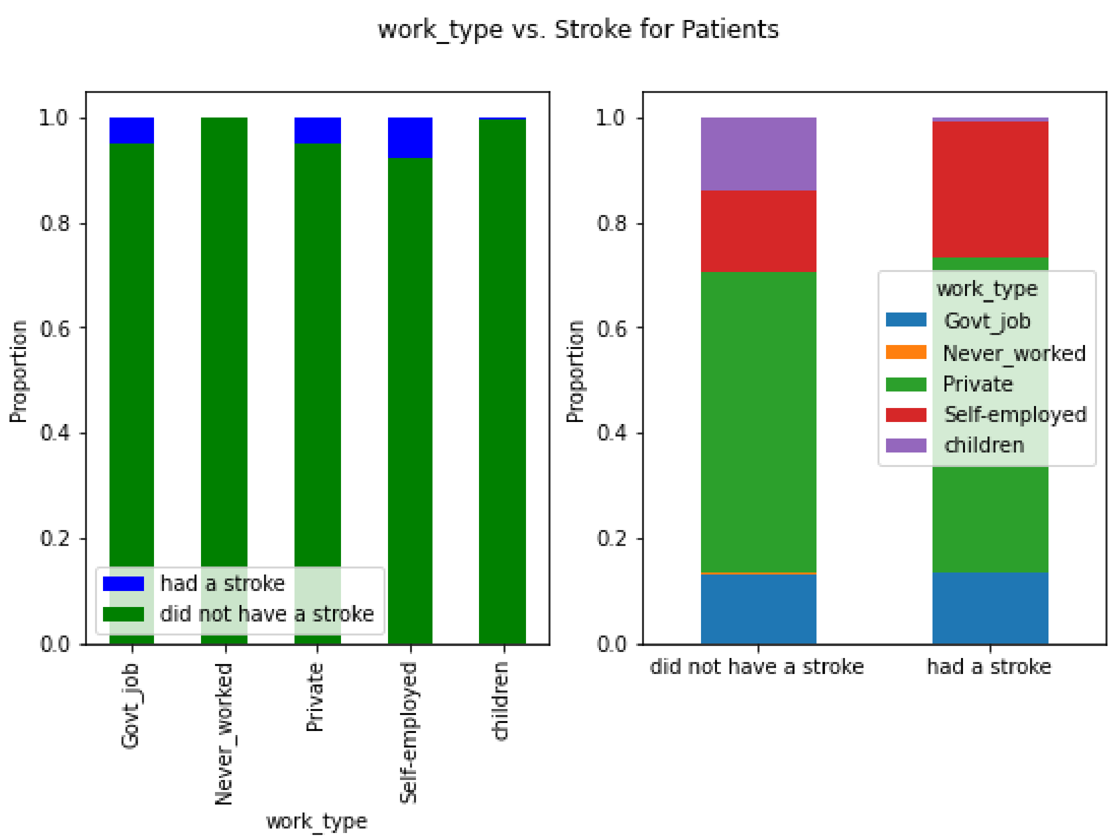
```
    ax[0].set_xlabel(cat_var)
    ax[0].set_ylabel("Proportion")
    color_patches = [
        Patch(facecolor="blue", label="had a stroke"),
        Patch(facecolor="green", label="did not have a stroke")
    ]
    ax[0].legend(handles=color_patches)

    tmp_feature_perc_df.plot(kind="bar", stacked=True, ax=ax[1])
    ax[1].legend(title=cat_var)
    ax[1].set_xticklabels(["did not have a stroke", "had a stroke"], rotation=0)
    ax[1].set_xlabel("")
    ax[1].set_ylabel("Proportion")

    fig.suptitle(f"{cat_var} vs. Stroke for Patients");
```

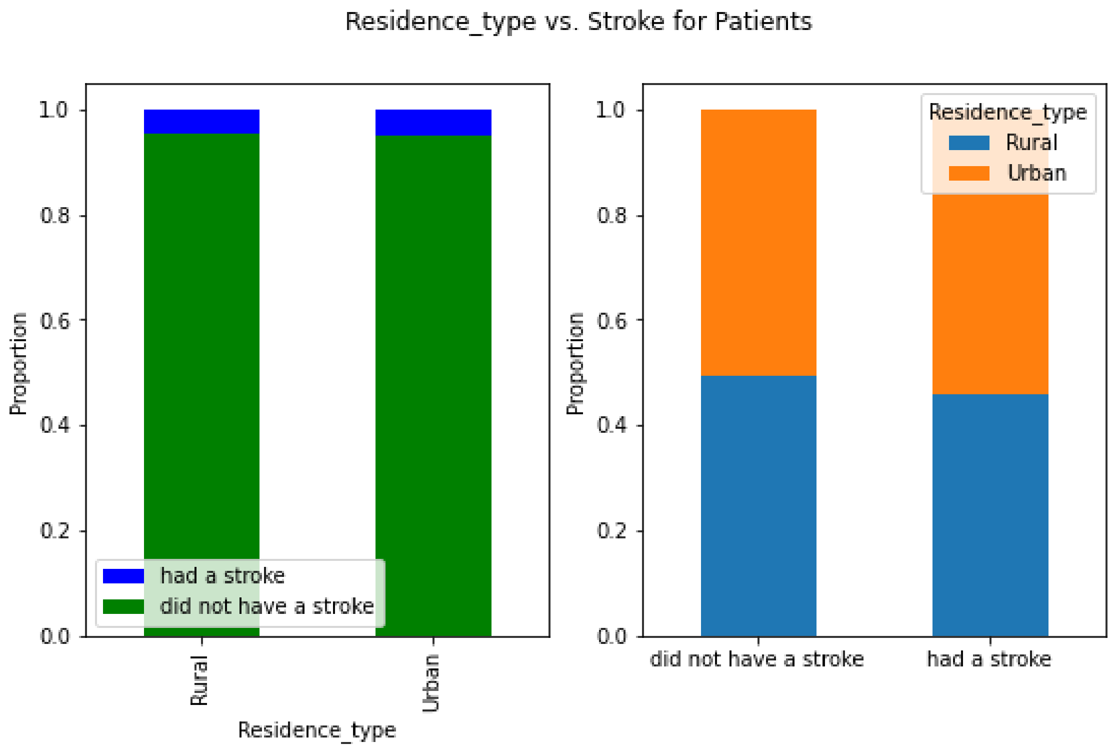


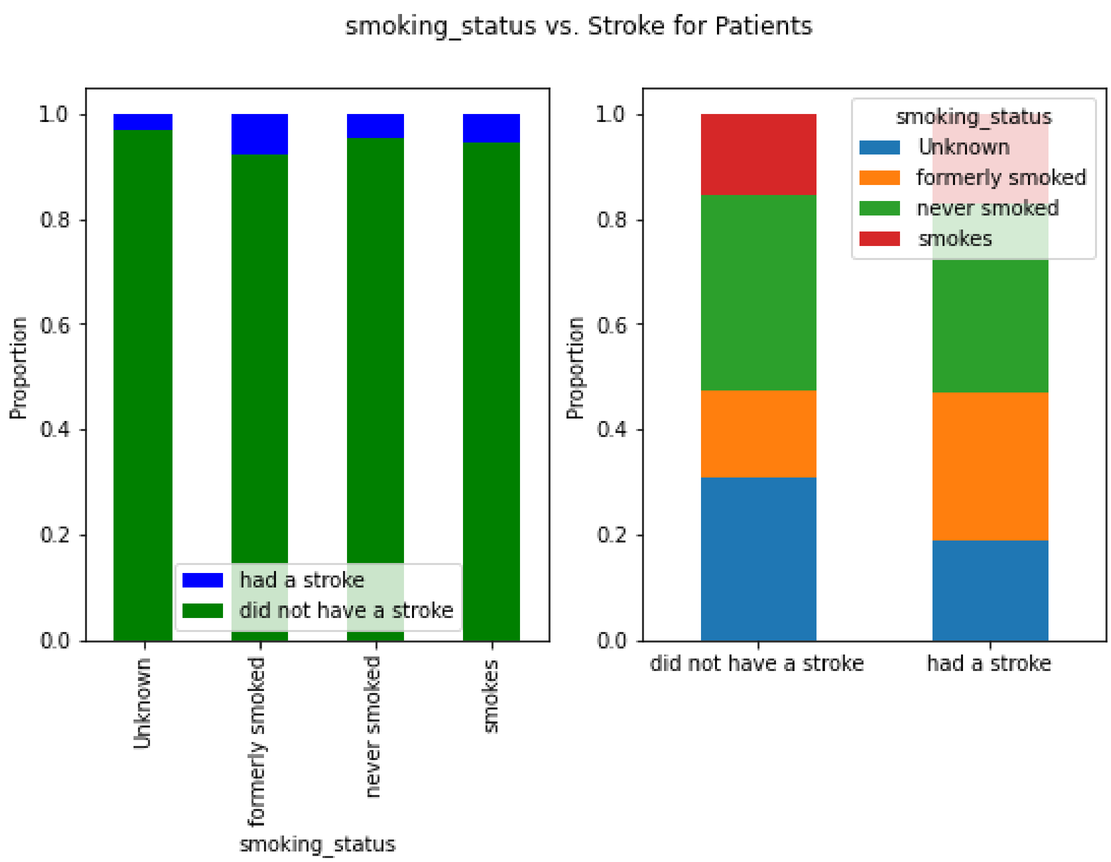

hypertension vs. Stroke for Patients
Proportion
1.0
0.8
0.6
0.4
0.2
0.0
had a stroke
did not have a stroke
0
1
hypertension
hypertension
0
1
did not have a stroke
had a stroke


heart_disease vs. Stroke for Patients
Proportion
1.0
0.8
0.6
0.4
0.2
0.0
had a stroke
did not have a stroke
0
1
heart_disease
heart_disease
0
1
did not have a stroke
had a stroke


ever_married vs. Stroke for Patients
Proportion
1.0
0.8
0.6
0.4
0.2
0.0
had a stroke
did not have a stroke
No
Yes
ever_married
ever_married
No
Yes
did not have a stroke
had a stroke


work_type vs. Stroke for Patients
Proportion
1.0
0.8
0.6
0.4
0.2
0.0
had a stroke
did not have a stroke
Govt_job
Never_worked
Private
Self-employed
children
work_type
work_type
Govt_job
Never_worked
Private
Self-employed
children
did not have a stroke
had a stroke

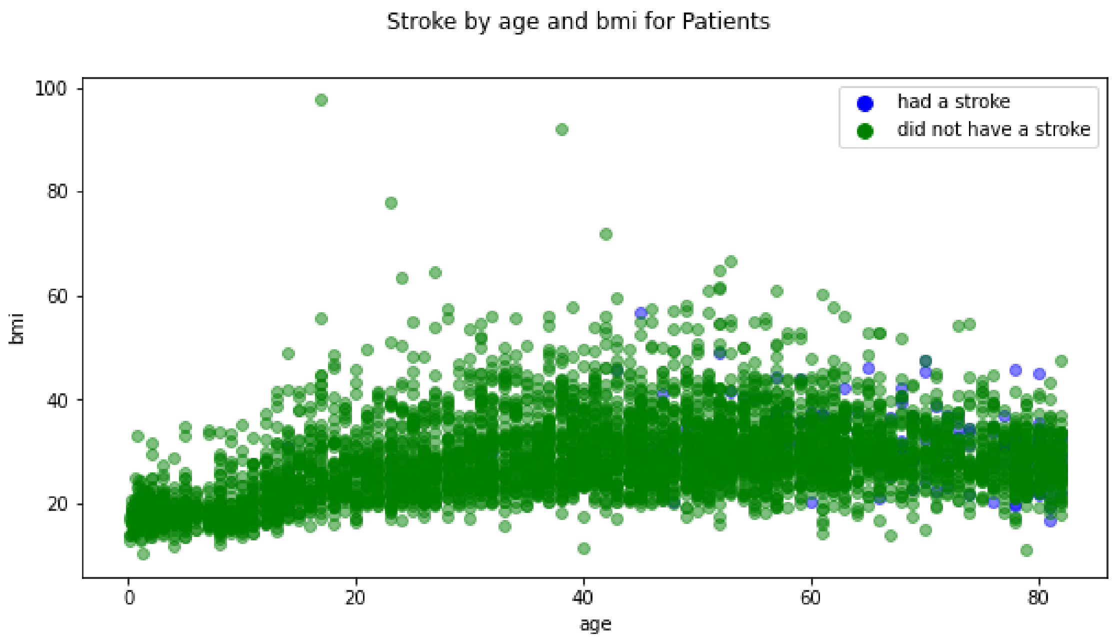

Residence_type vs. Stroke for Patients
Proportion
1.0
0.8
0.6
0.4
0.2
0.0
had a stroke
did not have a stroke
Rural
Urban
Residence_type
Residence_type
Rural
Urban
did not have a stroke
had a stroke

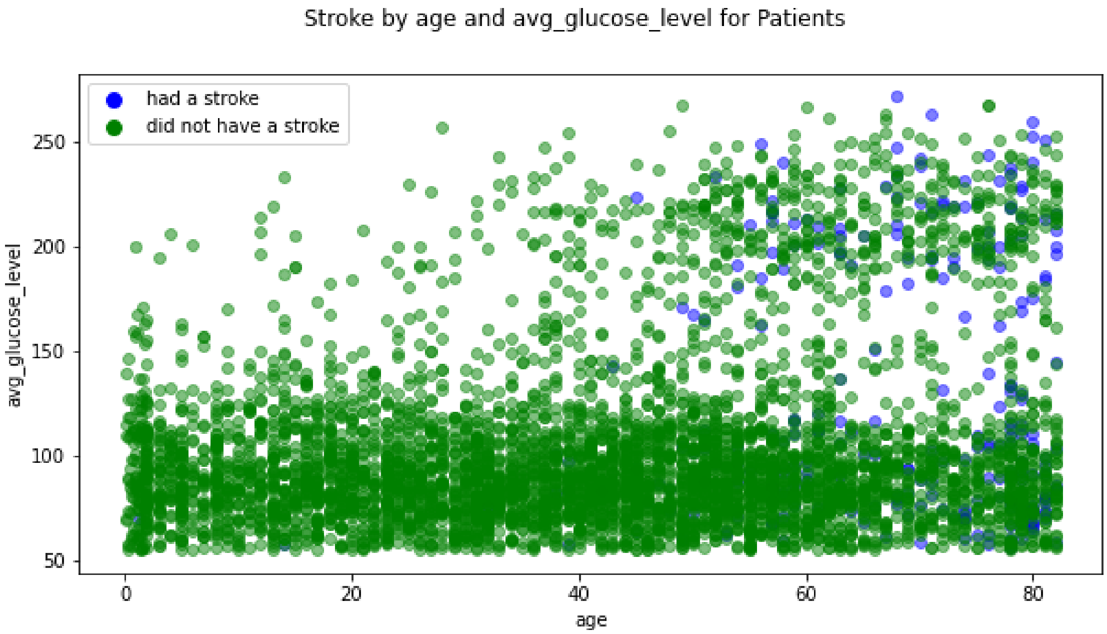


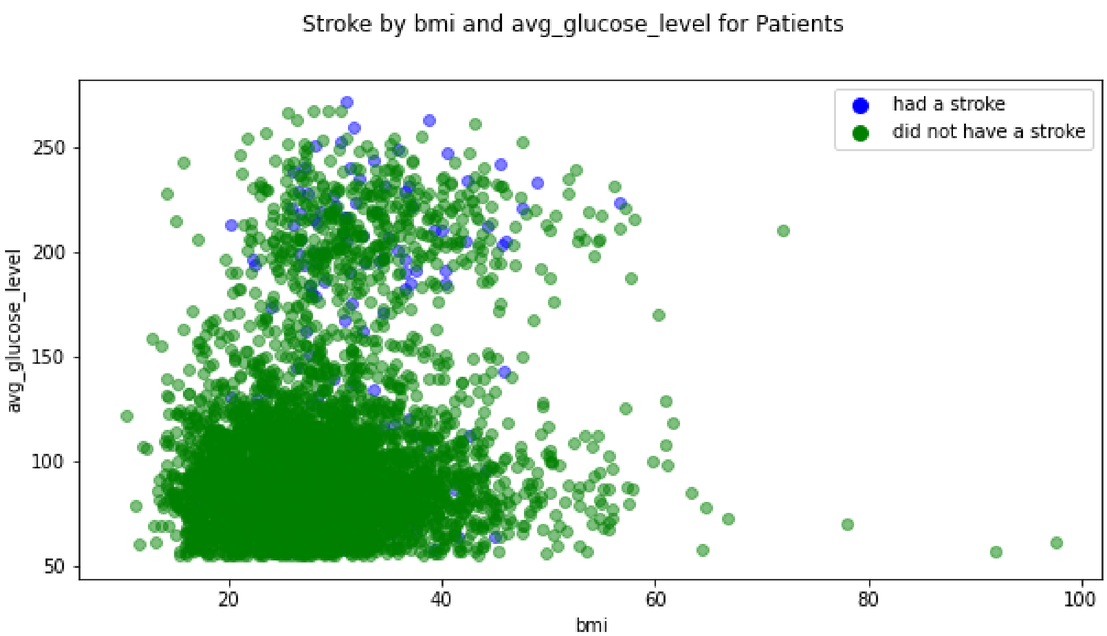
Numerical Variables

[22]:
```
combs = [("age","bmi"), ("age", "avg_glucose_level"), ("bmi",␣
↪"avg_glucose_level")]
target_var = "stroke"

for comb in combs:
    num_var1, num_var2 = comb
    fig, ax = plt.subplots(figsize=(10, 5))

    ax.scatter(dataframe[dataframe[target_var]==1][num_var1],␣
↪dataframe[dataframe[target_var]==1][num_var2], c="blue", alpha=0.5)
    ax.scatter(dataframe[dataframe[target_var]==0][num_var1],␣
↪dataframe[dataframe[target_var]==0][num_var2], c="green", alpha=0.5)

    ax.set_xlabel(num_var1)
    ax.set_ylabel(num_var2)

    color_patches = [
```

```
        Line2D([0], [0], marker='o', color='w', label='had a stroke',␣
↪markerfacecolor='b', markersize=10),
        Line2D([0], [0], marker='o', color='w', label='did not have a stroke',␣
↪markerfacecolor='g', markersize=10)
    ]
    ax.legend(handles=color_patches)

    fig.suptitle(f"Stroke by {num_var1} and {num_var2} for Patients");
```







0.3 Feature Engineering

After visualizing all of the features in our dataset, we notice some NaN values which we need to remove, we also need to normalize the numerical features as well as establish one-hot-encoded representations of the features. We might also be interested in removing the *Others* value for the gender as it represents 0.02% of the **gender** feature.

0.3.1 Gender Feature

For this feature, we remove the *Others* value

[23]:
```
# get the index of the row having "Other" as value for gender
Other_idx = dataframe.index[dataframe['gender']=="Other"].tolist()
dataframe_cleaned = dataframe.drop(Other_idx)
dataframe_cleaned
```

[23]:
```
      gender   age  hypertension  heart_disease ever_married      work_type  \
0       Male  67.0             0              1          Yes        Private
1     Female  61.0             0              0          Yes  Self-employed
2       Male  80.0             0              1          Yes        Private
3     Female  49.0             0              0          Yes        Private
4     Female  79.0             1              0          Yes  Self-employed
…        …     …             …              …          …              …
5105  Female  80.0             1              0          Yes        Private
5106  Female  81.0             0              0          Yes  Self-employed
5107  Female  35.0             0              0          Yes  Self-employed
5108    Male  51.0             0              0          Yes        Private
5109  Female  44.0             0              0          Yes       Govt_job

     Residence_type  avg_glucose_level   bmi   smoking_status  stroke
0             Urban             228.69  36.6  formerly smoked       1
1             Rural             202.21   NaN     never smoked       1
2             Rural             105.92  32.5     never smoked       1
3             Urban             171.23  34.4           smokes       1
4             Rural             174.12  24.0     never smoked       1
…                 …                  …     …              …       …
5105          Urban              83.75   NaN     never smoked       0
5106          Urban             125.20  40.0     never smoked       0
5107          Rural              82.99  30.6     never smoked       0
5108          Rural             166.29  25.6  formerly smoked       0
5109          Urban              85.28  26.2          Unknown       0

[5109 rows x 11 columns]
```

[24]:
```
# representing the categorical values after dropping
# get categorical data having multiple labels
categorical = categorical

categorical_df = pd.DataFrame()
for categorical_feature in categorical:
    tmp_df = pd.DataFrame({categorical_feature:
 ↪dataframe_cleaned[categorical_feature].unique()})
    categorical_df = pd.concat([categorical_df, tmp_df], axis=1)
```

```
categorical_df.fillna("", inplace= True)
categorical_df.head()
```

```
[24]:    gender hypertension heart_disease ever_married      work_type  \
      0    Male          0.0           1.0          Yes        Private
      1  Female          1.0           0.0           No  Self-employed
      2                                                        Govt_job
      3                                                        children
      4                                                    Never_worked

        Residence_type   smoking_status
      0          Urban  formerly smoked
      1          Rural     never smoked
      2                          smokes
      3                         Unknown
      4
```

0.3.2 BMI Feature

We will fill the NaN values with the mean values for the BMI features as there are 240+ datapoints with NaN values we might risk loosing important information.

```
[25]: dataframe_cleaned['bmi'].fillna((dataframe_cleaned['bmi'].mean()), inplace=
       ↪True)

vars_with_na = [col for col in dataframe_cleaned if dataframe_cleaned[col].
 ↪isnull().sum() > 0]
summarize_missingness(dataframe_cleaned[vars_with_na])
```

```
Empty DataFrame
Columns: [Count of missing/NaN values, Percentage of missing values]
Index: []
```

0.3.3 Feature Scaling

Feature scaling is the process of scaling numerical features either by min-max scaling or standardizations so that we keep our values in a defined range for each feature. - For standardization:

$$x_{stand} = \frac{x_{orig} - \mu}{\sigma}$$

where μ is the mean and σ is the standard deviation. - min-max scalar:

$$x_{norm} = \frac{x_{orig} - min}{max - min}$$

We will apply the min-max technique since our dataset distribution is not normal. As a result we will have values between 0 and 1.

```
[26]: cat_vars = categorical + ["stroke"]
# intialize output dataframe
```

```
dataframe_scaled = pd.DataFrame()

# separate categorical and numerical features into two different dataframes
dataframe_cleaned_cat = dataframe_cleaned[[c for c in dataframe_cleaned.columns␣
↪if c in cat_vars]]
dataframe_cleaned_num = dataframe_cleaned[[c for c in dataframe_cleaned.columns␣
↪if c in num_vars]]

# scale numerical values using Standard scalar
scaler = MinMaxScaler()
dataframe_scaled_num = pd.DataFrame(scaler.
↪fit_transform(dataframe_cleaned_num), columns= num_vars)

# reset index of categorical data points (index resets after scaling -␣
↪difference in scaling comes from removing "Others")
# data points from the dataset
dataframe_cleaned_cat = pd.DataFrame(np.array(dataframe_cleaned_cat), columns =␣
↪cat_vars)

# concatenating both dataframes
dataframe_scaled = pd.concat([dataframe_scaled_num, dataframe_cleaned_cat],␣
↪axis= 1)

# converting binary categories to int64 since after passing to array it's␣
↪transformed to Object
binary_cat = ["hypertension", "heart_disease", "stroke"]
dataframe_scaled[binary_cat] = dataframe_scaled[binary_cat].astype(np.int64)

dataframe_scaled
```

[26]:

```
           age  avg_glucose_level       bmi  gender  hypertension  \
0     0.816895           0.801265  0.301260    Male             0
1     0.743652           0.679023  0.212996  Female             0
2     0.975586           0.234512  0.254296    Male             0
3     0.597168           0.536008  0.276060  Female             0
4     0.963379           0.549349  0.156930  Female             1
…          …                …         …       …             …
5104  0.975586           0.132167  0.212996  Female             1
5105  0.987793           0.323516  0.340206  Female             0
5106  0.426270           0.128658  0.232532  Female             0
5107  0.621582           0.513203  0.175258    Male             0
5108  0.536133           0.139230  0.182131  Female             0

      heart_disease ever_married      work_type Residence_type  \
0                 1          Yes        Private          Urban
1                 0          Yes  Self-employed          Rural
```

```
2                   1           Yes        Private          Rural
3                   0           Yes        Private          Urban
4                   0           Yes  Self-employed          Rural
…                 …           …            …            …
5104                0           Yes        Private          Urban
5105                0           Yes  Self-employed          Urban
5106                0           Yes  Self-employed          Rural
5107                0           Yes        Private          Rural
5108                0           Yes       Govt_job          Urban

       smoking_status  stroke
0     formerly smoked       1
1        never smoked       1
2        never smoked       1
3              smokes       1
4        never smoked       1
…                 …     …
5104     never smoked       0
5105     never smoked       0
5106     never smoked       0
5107  formerly smoked       0
5108          Unknown       0

[5109 rows x 11 columns]
```

0.3.4 One-Hot-Encoding Non-Binary Categorical Features

[27]:
```python
dataframe_ohe_scaled = pd.get_dummies(data= dataframe_scaled)
dataframe_ohe_scaled
```

[27]:
```
           age  avg_glucose_level       bmi  hypertension  heart_disease  \
0     0.816895           0.801265  0.301260             0              1
1     0.743652           0.679023  0.212996             0              0
2     0.975586           0.234512  0.254296             0              1
3     0.597168           0.536008  0.276060             0              0
4     0.963379           0.549349  0.156930             1              0
…          …                 …        …           …            …
5104  0.975586           0.132167  0.212996             1              0
5105  0.987793           0.323516  0.340206             0              0
5106  0.426270           0.128658  0.232532             0              0
5107  0.621582           0.513203  0.175258             0              0
5108  0.536133           0.139230  0.182131             0              0

      stroke  gender_Female  gender_Male  ever_married_No  ever_married_Yes  \
0          1              0            1                0                 1
1          1              1            0                0                 1
2          1              0            1                0                 1
```

```
3        1           1          0             0              1
4        1           1          0             0              1
…       …          …         …            …             …
5104     0           1          0             0              1
5105     0           1          0             0              1
5106     0           1          0             0              1
5107     0           0          1             0              1
5108     0           1          0             0              1

      …  work_type_Never_worked  work_type_Private  work_type_Self-employed  \
0     …                       0                  1                        0
1     …                       0                  0                        1
2     …                       0                  1                        0
3     …                       0                  1                        0
4     …                       0                  0                        1
…   …                     …                …                      …
5104  …                       0                  1                        0
5105  …                       0                  0                        1
5106  …                       0                  0                        1
5107  …                       0                  1                        0
5108  …                       0                  0                        0

      work_type_children  Residence_type_Rural  Residence_type_Urban  \
0                      0                     0                     1
1                      0                     1                     0
2                      0                     1                     0
3                      0                     0                     1
4                      0                     1                     0
…                    …                   …                   …
5104                   0                     0                     1
5105                   0                     0                     1
5106                   0                     1                     0
5107                   0                     1                     0
5108                   0                     0                     1

      smoking_status_Unknown  smoking_status_formerly smoked  \
0                          0                               1
1                          0                               0
2                          0                               0
3                          0                               0
4                          0                               0
…                        …                             …
5104                       0                               0
5105                       0                               0
5106                       0                               0
5107                       0                               1
5108                       1                               0
```

```
      smoking_status_never smoked  smoking_status_smokes
0                               0                      0
1                               1                      0
2                               1                      0
3                               0                      1
4                               1                      0
…                             …                    …
5104                            1                      0
5105                            1                      0
5106                            1                      0
5107                            0                      0
5108                            0                      0

[5109 rows x 21 columns]
```

0.3.5 Getting Feature Matrix and Target Vector

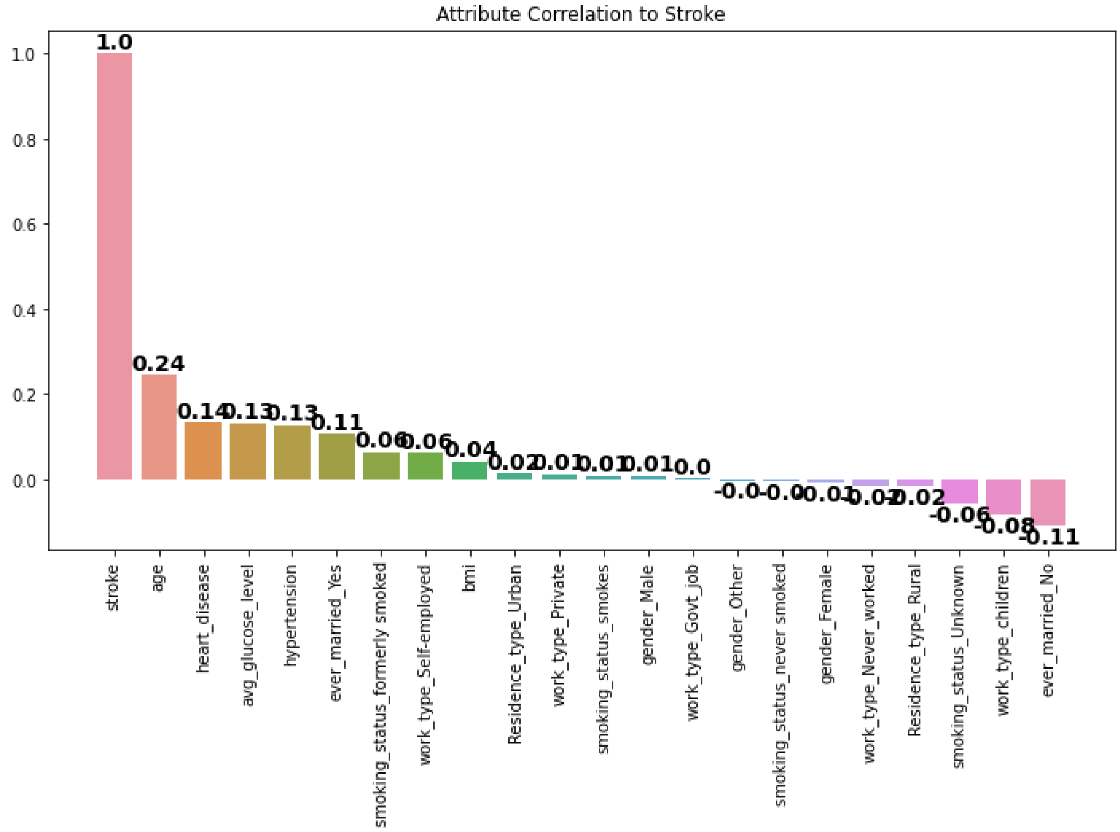
[28]:
```
X = dataframe_ohe_scaled.drop("stroke", axis= 1) #Feature Matrix
y = dataframe_ohe_scaled["stroke"] #Target Variable
```

0.3.6 Using Correlation to Filter-Out Features

From the calculated correlation matrix, we are able to filter-out low-correlation features with the target since they do not provide any information with regards to the target.

[29]:
```
corr_matrix = cor.round(3)
corr_target = corr_matrix['stroke'].sort_values(ascending=False)

fig, ax = plt.subplots(figsize=(12,6))

sns.barplot(x=corr_target.index, y=corr_target.values, ax=ax)

ax.grid(False)
ax.set_title('Attribute Correlation to Stroke')
plt.setp(ax.get_xticklabels(), rotation=90)

for n, x in enumerate(corr_target.index):
    if corr_target[n] >= 0:
        ax.text(x=n, y=corr_target[n], s=corr_target[n].round(2),
            horizontalalignment='center', verticalalignment='bottom',
            fontsize=14, fontweight='bold')
    else:
        ax.text(x=n, y=corr_target[n], s=corr_target[n].round(2),
            horizontalalignment='center', verticalalignment='top',
            fontsize=14, fontweight='semibold')
```

```python
ax.axis('tight')

plt.show()
```



We can select the following features having the highest correlation with respect to the target: - age - heart_disease - avg_glucose_level

We can also select some others having some lower correlations but provide information about the targets: - hypertension - ever_married (Yes/No)

[30]:
```python
X_filtered = X[["age", "hypertension", "heart_disease", "avg_glucose_level",␣
↪"ever_married_No", "ever_married_Yes"]]
y = dataframe_ohe_scaled["stroke"]
X_filtered
```

[30]:
```
        age  hypertension  heart_disease  avg_glucose_level  \
0  0.816895             0              1           0.801265
1  0.743652             0              0           0.679023
2  0.975586             0              1           0.234512
3  0.597168             0              0           0.536008
4  0.963379             1              0           0.549349
```

```
...      ...              ...              ...                  ...
5104  0.975586           1               0              0.132167
5105  0.987793           0               0              0.323516
5106  0.426270           0               0              0.128658
5107  0.621582           0               0              0.513203
5108  0.536133           0               0              0.139230

      ever_married_No  ever_married_Yes
0                   0                 1
1                   0                 1
2                   0                 1
3                   0                 1
4                   0                 1
...               ...               ...
5104                0                 1
5105                0                 1
5106                0                 1
5107                0                 1
5108                0                 1

[5109 rows x 6 columns]
```

It is important to note that we can also keep the remaining features but after some performed experiments, fitlering features increased the model performance as we removed noisy data which did not contribute to the target prediction.

0.4 Model Training

To train any machine learning model, we must follow the steps below: 1. obtain a processed dataset with relevant features - split into train/val/test 2. define project/model metrics based on which we benchmark models - either accuracy, precision, recall, f1-score or ROC curve 3. select an appropriate model to best fit our data 4. train a model and evaluate performance based on validation data and metrics 5. test model on testing data 6. if we need some improvements thorugh hyperparameter tuning we repeat from step 3

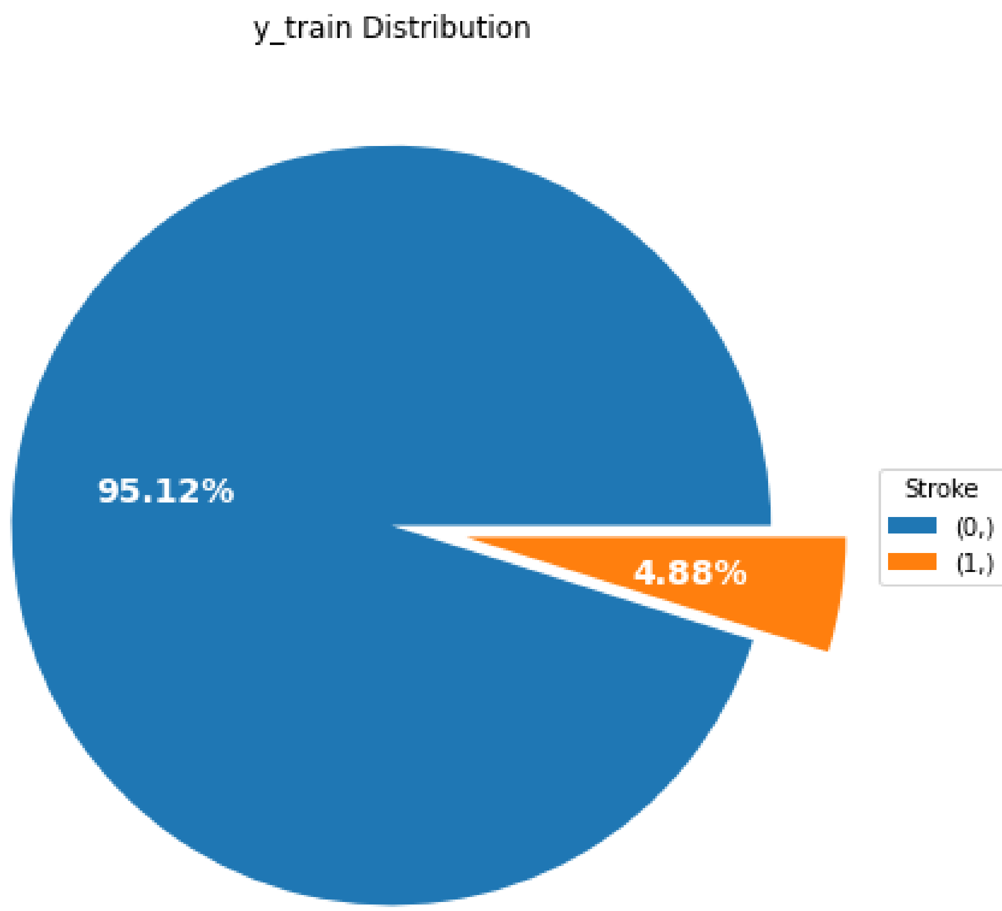
0.4.1 Splitting The Dataset

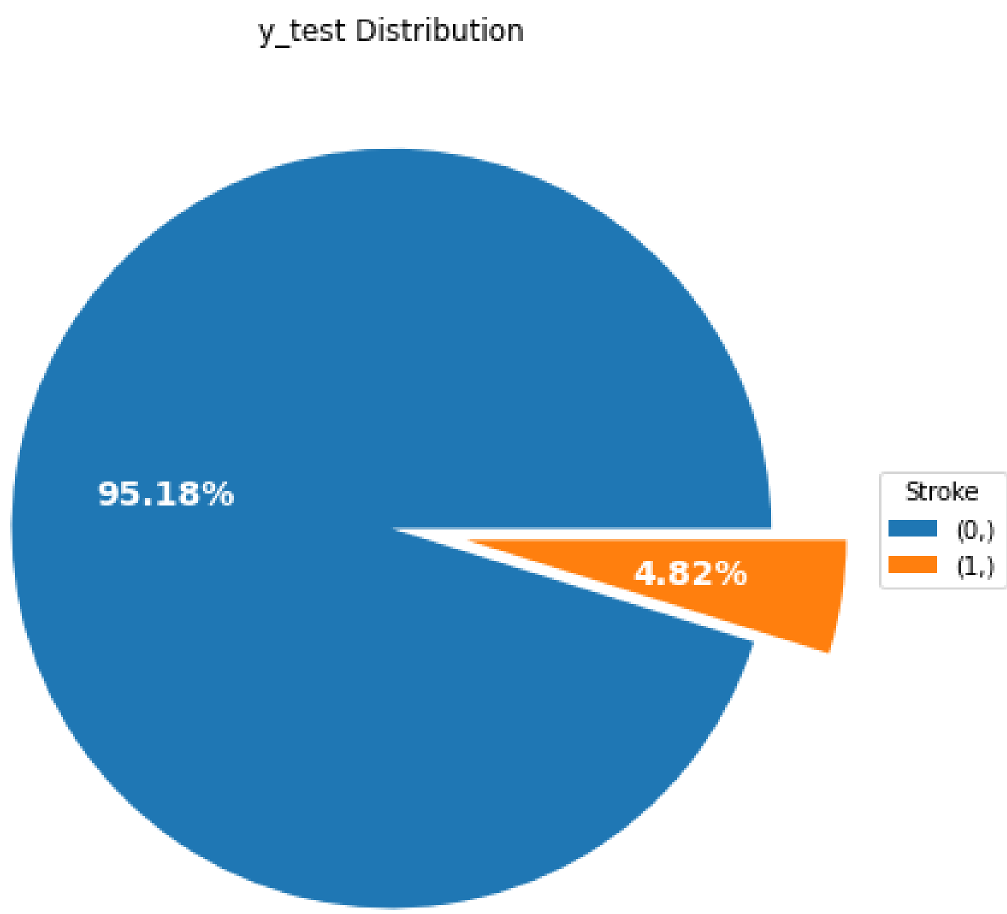
[31]:
```python
# set seed
SEED = 100

# separate data into train and test
# test_size= 0.15 => 15% testing 85% training
# Fix the seed to the random generator
X_train, X_test, y_train, y_test = train_test_split(np.array(X_filtered), np.
 ↪array(y), test_size=0.15, random_state=SEED)

print(f"Shape of training features {X_train.shape}")
print(f"Shape of test features {X_test.shape}")
```

```
print(f"Shape of training targets {y_train.shape}")
print(f"Shape of testing targets {y_test.shape}")
```

```
Shape of training features (4342, 6)
Shape of test features (767, 6)
Shape of training targets (4342,)
Shape of testing targets (767,)
```

[32]:
```
vis_target_dist(pd.DataFrame(y_train), "y_train Distribution")
vis_target_dist(pd.DataFrame(y_test), "y_test Distribution")

plt.show()
```





0.4.2 Metrics To Consider

Confusion Matrix, Precision, Recall, f1-score, Precision-recall curve.

[33]:
```
def construct_classification_report(y_true, y_pred):
    cm = confusion_matrix(y_true, y_pred)
    cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
    diag_cm = cm.diagonal()
    class_pos_acc = diag_cm[0]
    class_neg_acc = diag_cm[1]

    balanced_acc = (class_neg_acc + class_pos_acc)/2

    cr = classification_report(y_true, y_pred)
    aug_cr = cr[:53] + "\taccuracy" + cr[53:108] + f"\t    {class_pos_acc:.2f}"␣
 ↪+ cr[108:162]\
```

```
        + f"\t    {class_neg_acc:.2f}" + cr[162:217] + f"\tbalanced accuracy:␣
↪{balanced_acc:.2f}" + cr[217:]

    return aug_cr
```

[34]:
```
def vis_metrics(y_true, y_pred, model_name= None):

    print(construct_classification_report(y_true, y_pred))

    disp = ConfusionMatrixDisplay.from_predictions(y_true, y_pred, labels= [1,␣
↪0])
    disp.ax_.set_title("Confusion Matrix")


    # plot PR curve
    disp = PrecisionRecallDisplay.from_predictions(y_true, y_pred, pos_label=␣
↪1, name= model_name)
    disp.ax_.set_title("P-R Curve")

    disp = RocCurveDisplay.from_predictions(y_true, y_pred, pos_label= 1, name=␣
↪model_name)
    disp.ax_.set_title("ROC Curve")
```

0.4.3 Model Training

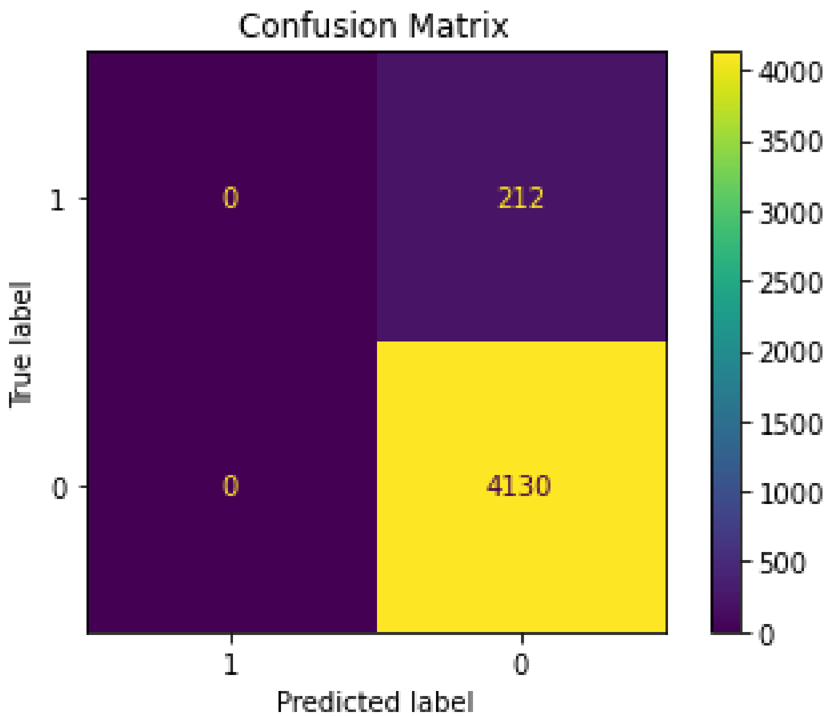
In this part, we will implement 3 models for classification: - Random Forest - Logistic Regression - Multi-Layered Perceptron (Neural Network)

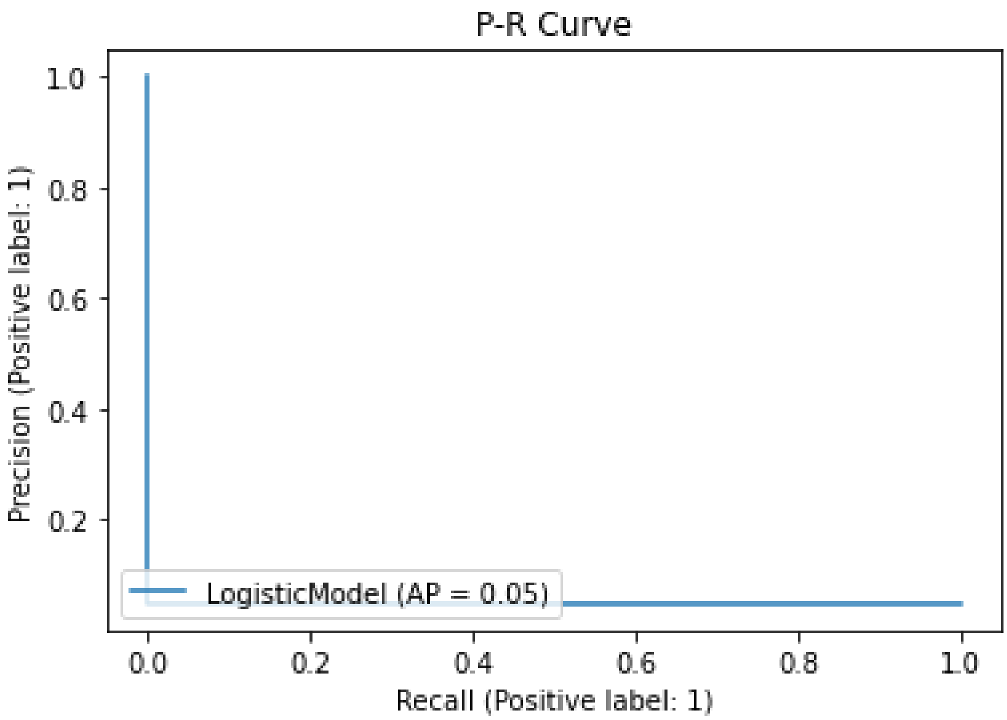
Logistic Regression Model

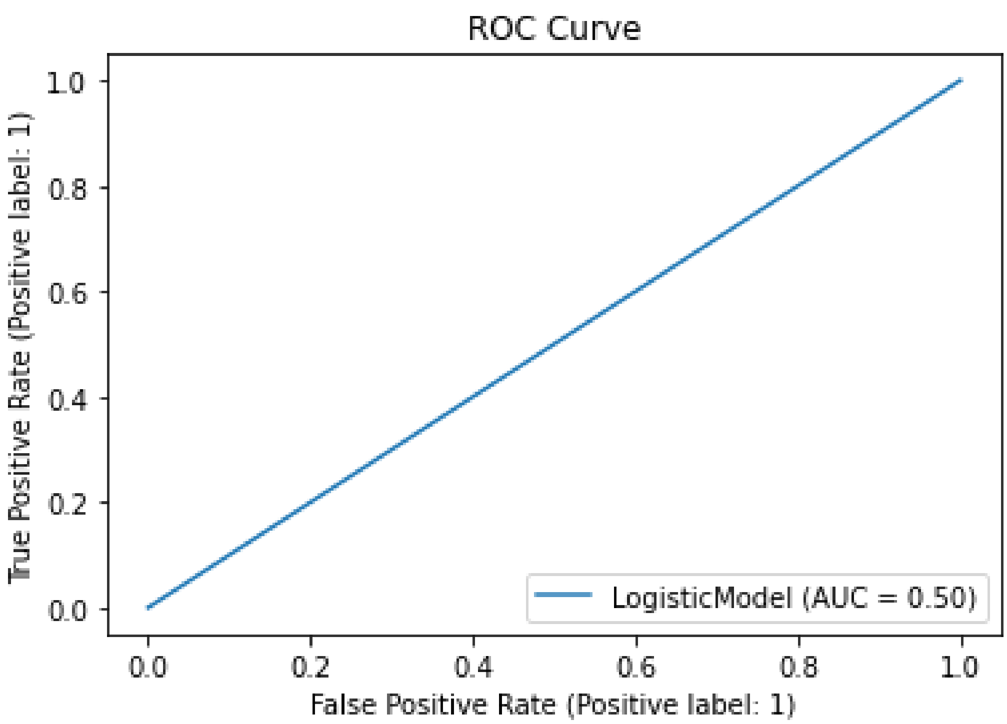
[35]:
```
logistic_model = LogisticRegression(max_iter= 1000)
logistic_model.fit(X_train, y_train)

# Predicting on the test data
pred_normal = logistic_model.predict(X_train)

vis_metrics(y_train, pred_normal, "LogisticModel")
plt.show()
```

```
              precision    recall  f1-score   support   accuracy

           0       0.95      1.00      0.97      4130       1.00
           1       0.00      0.00      0.00       212       0.00

    accuracy                           0.95      4342   balanced accuracy: 0.50
   macro avg       0.48      0.50      0.49      4342
weighted avg       0.90      0.95      0.93      4342
```

```
C:\Users\Charb\anaconda3\envs\ml\lib\site-
packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\Charb\anaconda3\envs\ml\lib\site-
packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\Charb\anaconda3\envs\ml\lib\site-
packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```




P-R Curve
1.0
0.8
0.6
0.4
0.2
Precision (Positive label: 1)
LogisticModel (AP = 0.05)
0.0
0.2
0.4
0.6
0.8
1.0
Recall (Positive label: 1)


ROC Curve
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate (Positive label: 1)
LogisticModel (AUC = 0.50)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (Positive label: 1)

We note that the performance of this model is rather low with no regard to our positive class which is a patient having a stroke. This target is our main objective and low performance on that target should not be accepted for this model. This low performance comes from the fact that our target distribution from the training set is not balanced. Thus the learning process favors the overall accuracy but not one class accuracy. We will use the following methods to try and counter this issue: - **Assigning Class Weights**: it's the process of assigning weights to each of the target classes favoring one class over the other during training; the class with the higher weight will impose a larger penalty on the model. - **Over-sampling**: Oversampling is the process of randomly resampling the training dataset (and not the test set) in a way to favor the minority class and increase its representation in the training set. We will implement two methods: Random and ADASYN by using the *imbalanced-learn* library.

These methods will be implemented for all 3 training models.

Logistic Regression Model with Weighted Classes

Obtaining Class Weights Available scoring metrics to obtain the best class weights.

[36]:
```
def get_class_weights(X_train, y_train, scoring= 'f1'):
    lr = LogisticRegression(solver='newton-cg')

    #Setting the range for class weights
    weights = np.linspace(0.0,0.99,200)

    #Creating a dictionary grid for grid search
    param_grid = {'class_weight': [{0:x, 1:1.0-x} for x in weights]}

    #Fitting grid search to the train data with 5 folds
    gridsearch = GridSearchCV(estimator= lr,
                              param_grid= param_grid,
                              cv=StratifiedKFold(),
                              n_jobs=-1,
                              scoring= scoring,
                              verbose=2).fit(X=X_train, y=y_train)

    #Ploting the score for different values of weight
    sns.set_style('whitegrid')
    fig, ax = plt.subplots()

    weigh_data = pd.DataFrame({ 'score': gridsearch.
 ↪cv_results_['mean_test_score'], 'weight': (1- weights)})

    x, y = weigh_data['weight'], weigh_data['score']

    def annot_max(x,y, ax=None):
        xmax = x[np.argmax(y)]
        ymax = y.max()
        text= "x={:.3f}, y={:.3f}".format(xmax, ymax)
```

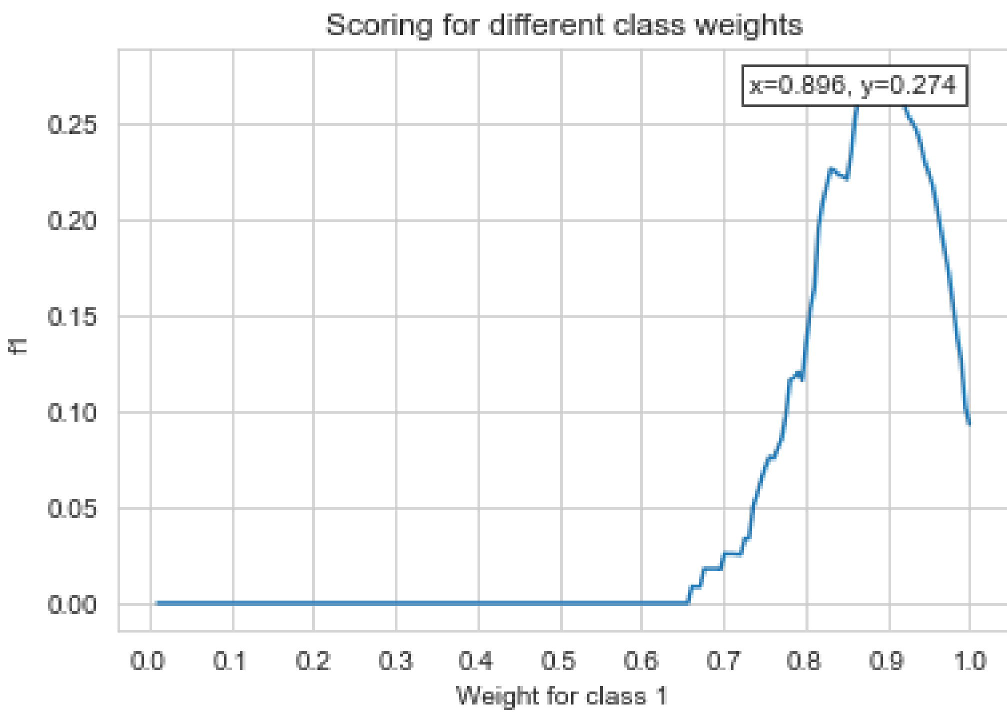
```
        if not ax:
            ax=plt.gca()
        bbox_props = dict(boxstyle="square,pad=0.3", fc="w", ec="k", lw=0.72)
       ␣
↪arrowprops=dict(arrowstyle="->",connectionstyle="angle,angleA=0,angleB=60")
        kw = dict(xycoords='data',textcoords="axes fraction",
                  arrowprops=arrowprops, bbox=bbox_props, ha="right", va="top")
        ax.annotate(text, xy=(xmax, ymax), xytext=(0.94,0.96), **kw)

        return xmax, ymax

    sns.lineplot(x, y)
    xmax, ymax = annot_max(x,y)
    plt.xlabel('Weight for class 1')
    plt.ylabel(scoring)
    plt.xticks([round(i/10,1) for i in range(0,11,1)])
    plt.title('Scoring for different class weights')
    plt.show()

    return xmax, ymax
```

[37]:
```
scoring = 'f1'
#sklearn.metrics.SCORERS.keys() Scoring techniques can be shown from this output
```

[38]:
```
xmax, ymax = get_class_weights(X_train, y_train, scoring= scoring)
```

```
Fitting 5 folds for each of 200 candidates, totalling 1000 fits
```

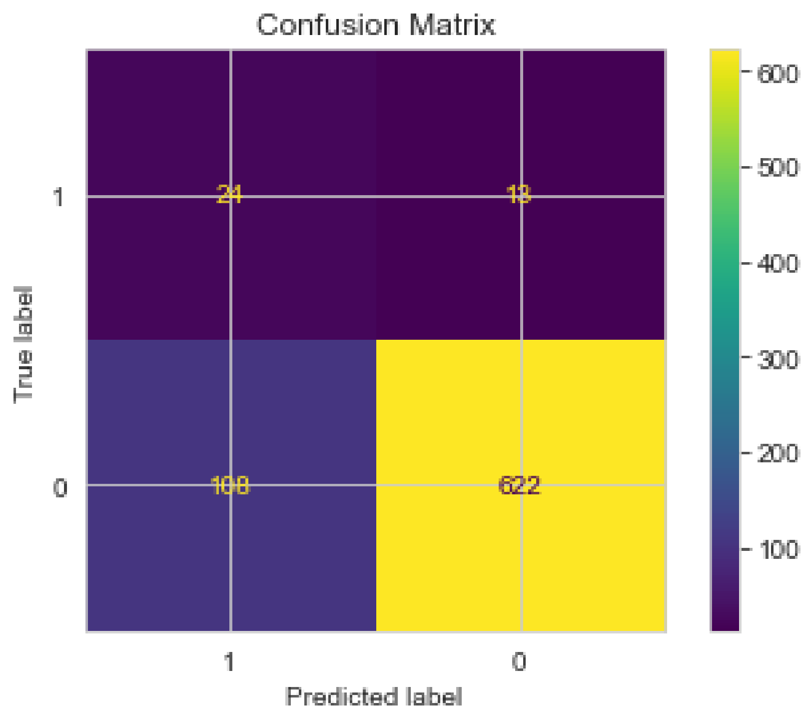
```
C:\Users\Charb\anaconda3\envs\ml\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variables as keyword args: x, y. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
```

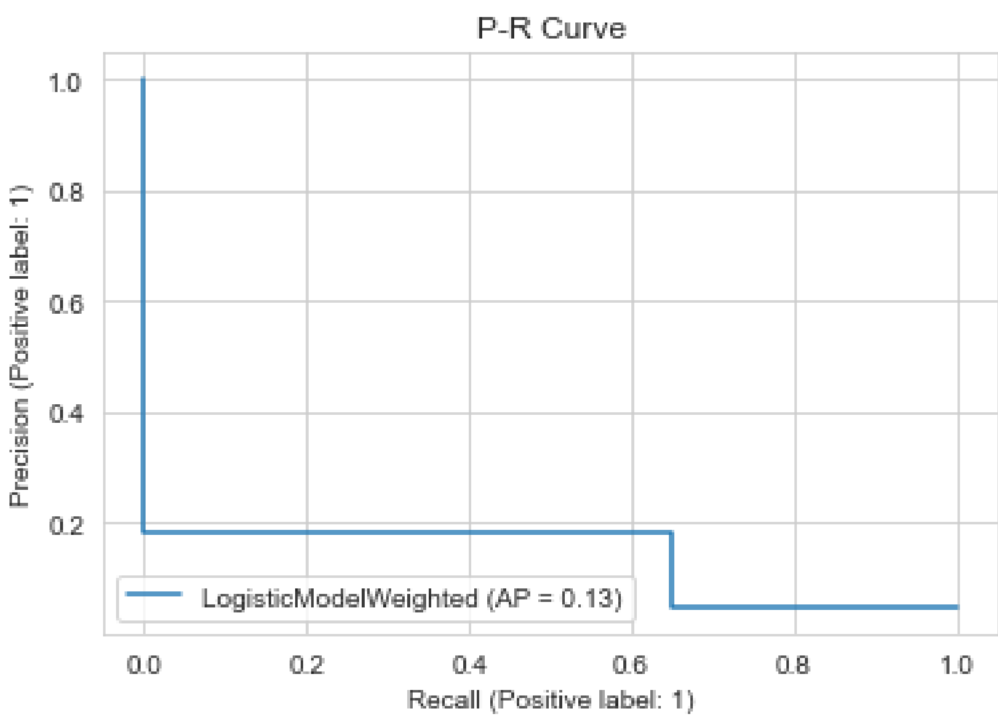


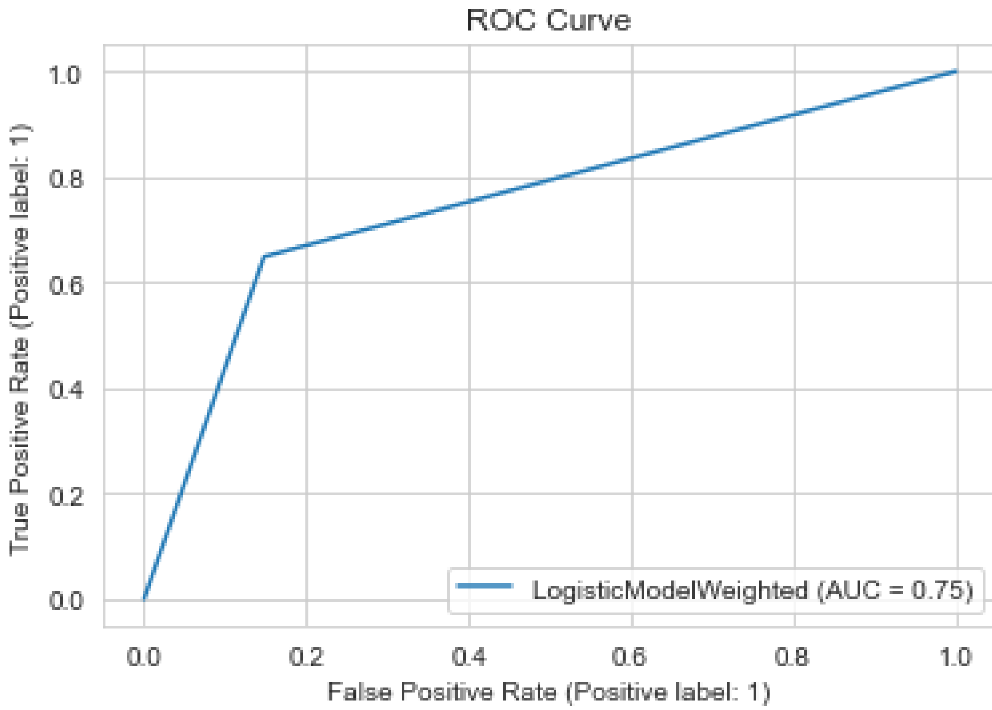
Logistic Regression Model Trainning + Metrics Visualization

[39]:
```
logistic_model = LogisticRegression(solver='newton-cg', class_weight={0: (0.
↪99-xmax), 1:xmax}, max_iter= 1000)
logistic_model.fit(X_train, y_train)

# Predicting on the test data
pred_weighted = logistic_model.predict(X_test)

vis_metrics(y_test, pred_weighted, "LogisticModelWeighted")
plt.show()
```

```
              precision    recall  f1-score   support   accuracy

           0       0.98      0.85      0.91       730       0.85
           1       0.18      0.65      0.28        37       0.65

    accuracy                           0.84       767   balanced accuracy: 0.75
   macro avg       0.58      0.75      0.60       767
weighted avg       0.94      0.84      0.88       767
```


Confusion Matrix
True label
Predicted label
1
0
1
0
24
13
108
622
600
500
400
300
200
100

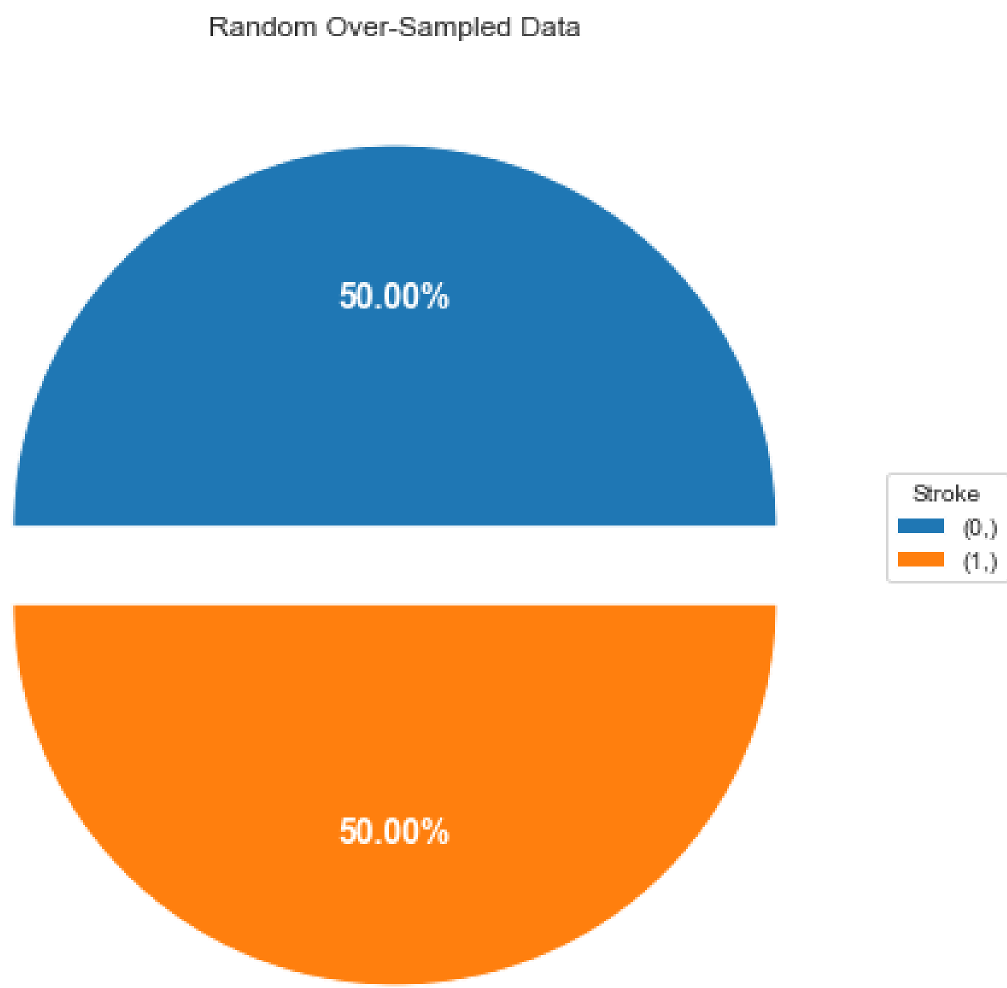

P-R Curve
Precision (Positive label: 1)
Recall (Positive label: 1)
LogisticModelWeighted (AP = 0.13)
1.0
0.8
0.6
0.4
0.2
0.0
0.2
0.4
0.6
0.8
1.0



Over-Sampling Dataset - Random

[40]:
```
ros = RandomOverSampler(random_state=0)
X_train_ros, y_train_ros = ros.fit_resample(X_train, y_train)
```

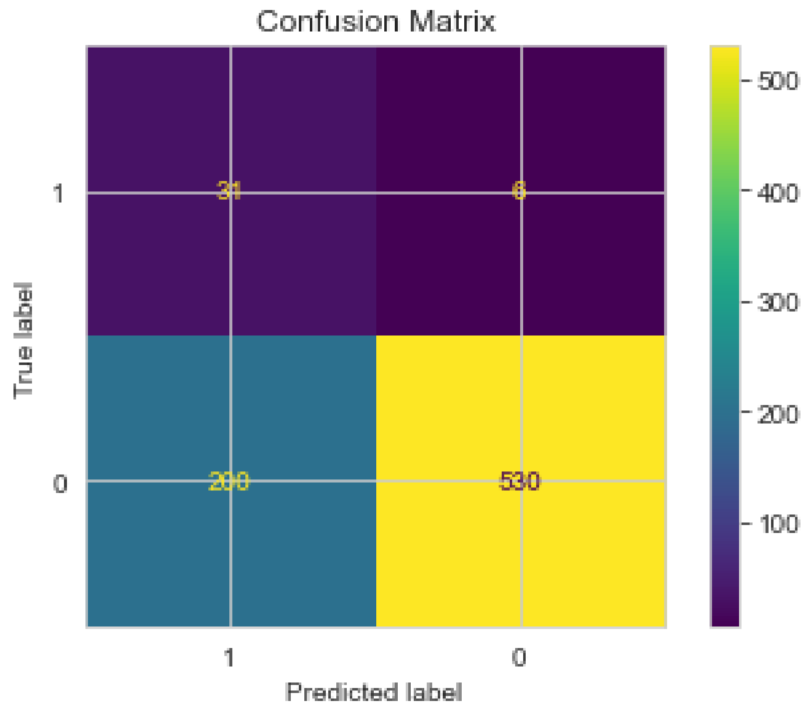
[41]:
```
vis_target_dist(pd.DataFrame(y_train_ros), "Random Over-Sampled Data")
```

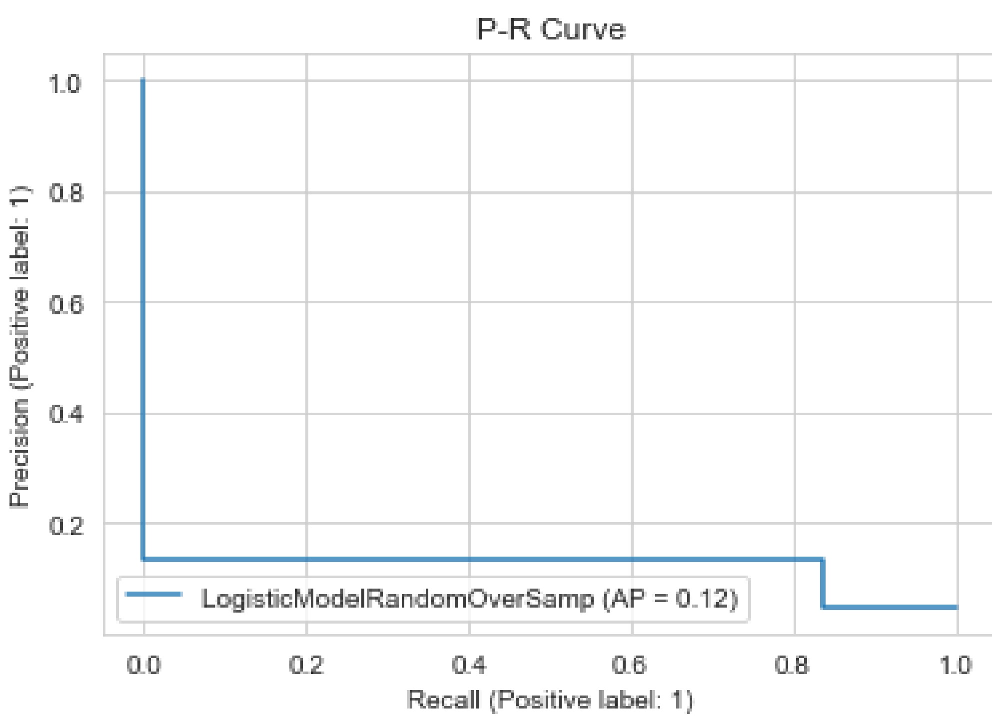


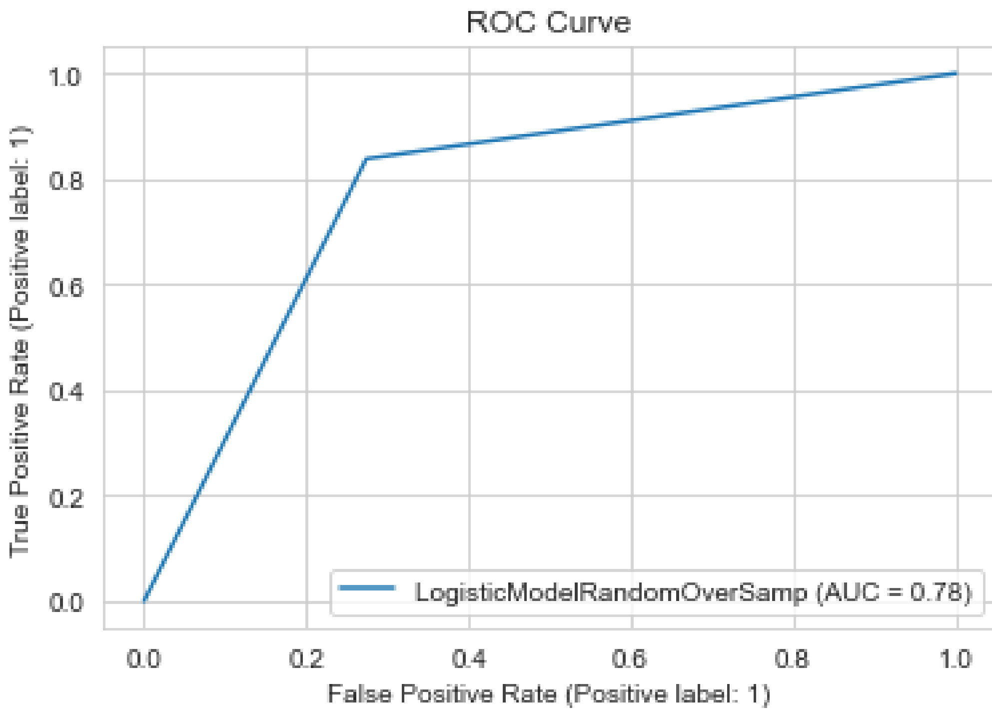
[42]:
```
logistic_model = LogisticRegression(solver='newton-cg', max_iter= 1000)
logistic_model.fit(X_train_ros, y_train_ros)

# Predicting on the test data
pred_rand_overs = logistic_model.predict(X_test)

vis_metrics(y_test, pred_rand_overs, "LogisticModelRandomOverSamp")
plt.show()
```

```
              precision    recall  f1-score   support   accuracy

           0       0.99      0.73      0.84       730       0.73
           1       0.13      0.84      0.23        37       0.84

    accuracy                           0.73       767   balanced accuracy: 0.78
   macro avg       0.56      0.78      0.53       767
```

```
weighted avg       0.95      0.73      0.81       767
```



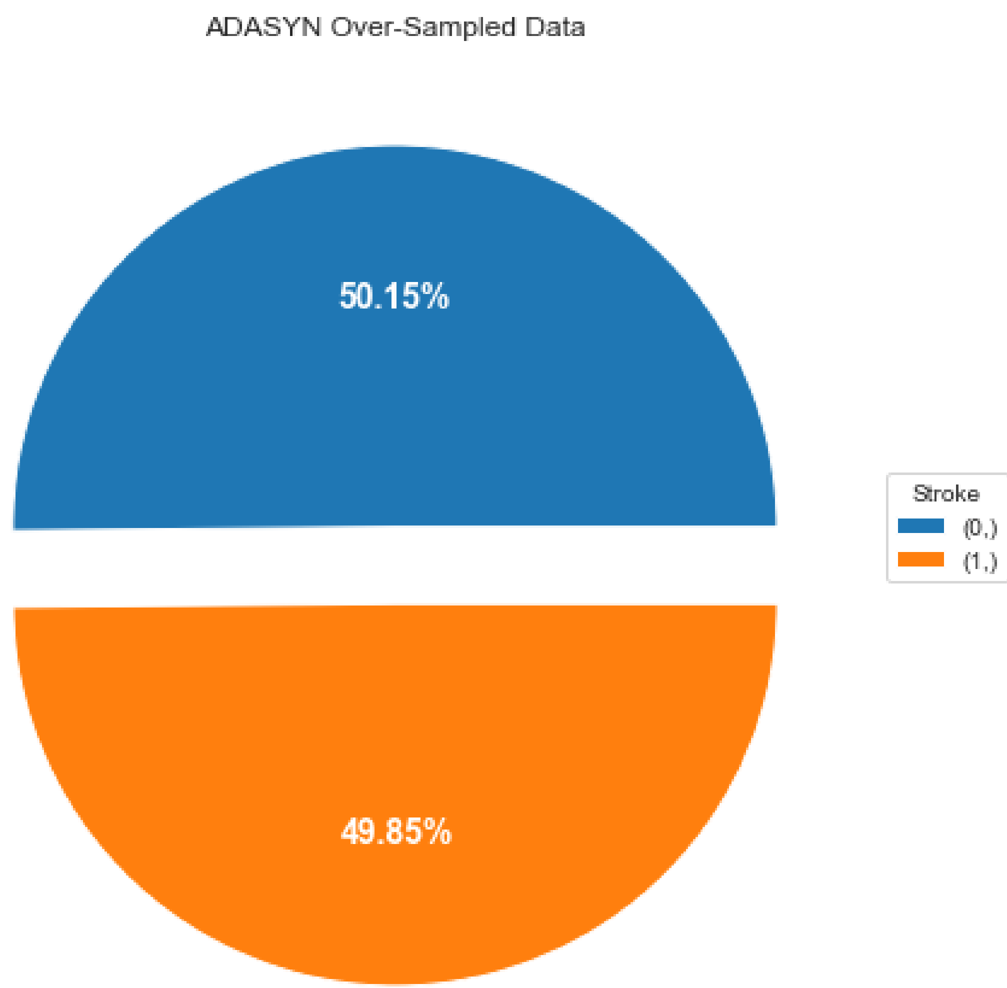




Over-Sampling Dataset - ADASYN

[43]:
```
X_train_adasyn, y_train_adasyn = ADASYN().fit_resample(X_train, y_train)
```

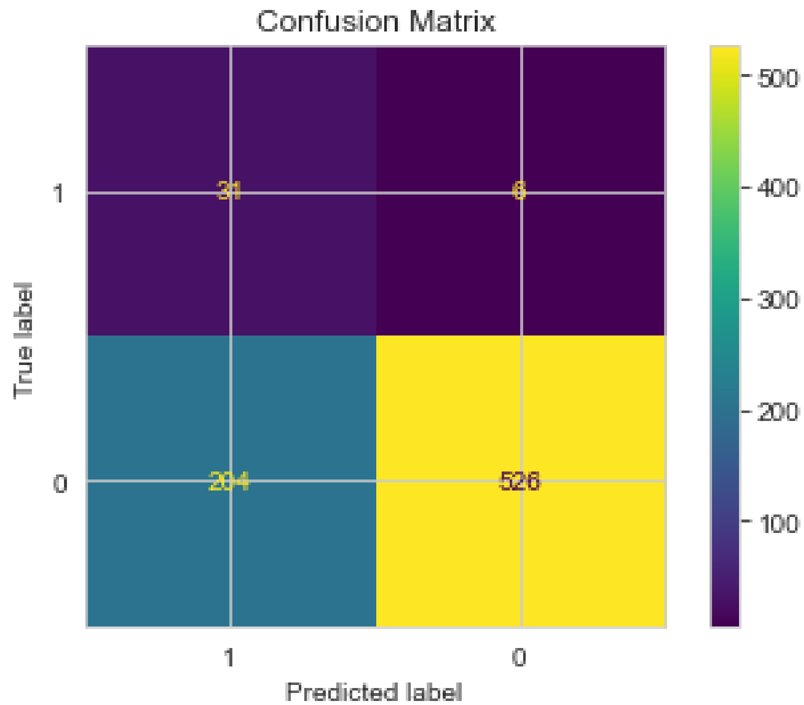
[44]:
```
vis_target_dist(pd.DataFrame(y_train_adasyn), "ADASYN Over-Sampled Data")
```

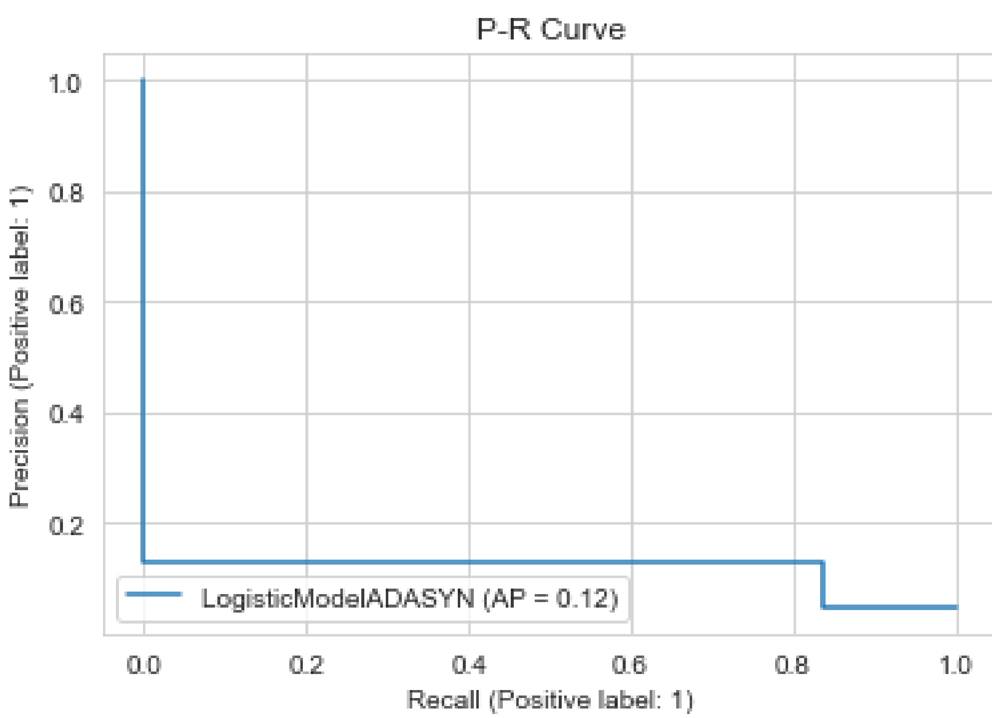


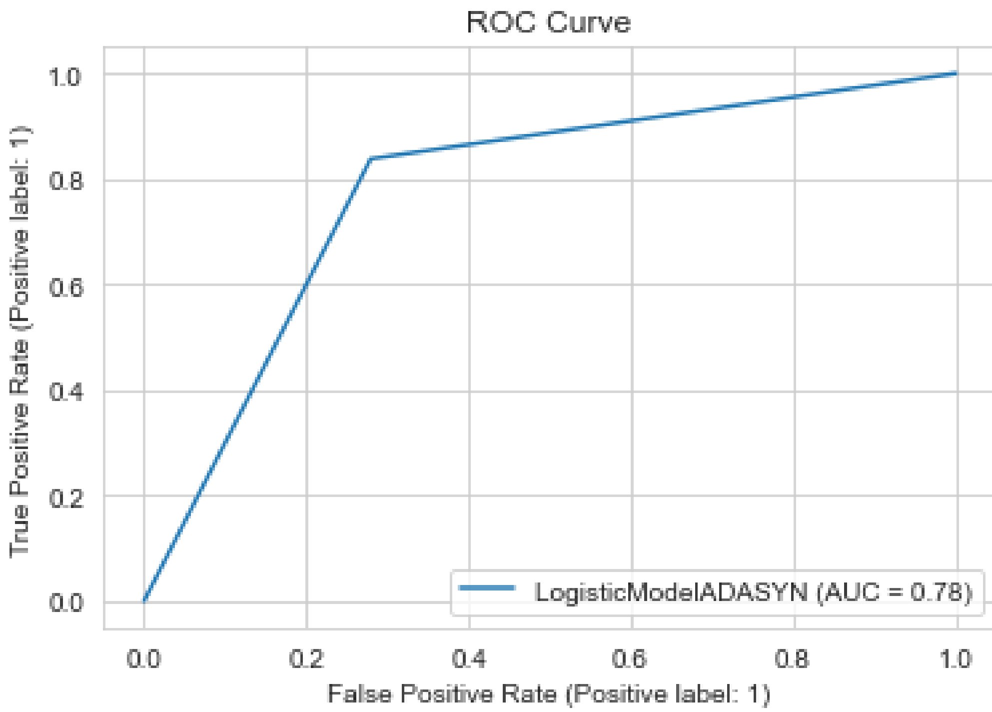
[45]:
```
logistic_model = LogisticRegression(solver='newton-cg', max_iter= 1000)
logistic_model.fit(X_train_adasyn, y_train_adasyn)

# Predicting on the test data
pred_adasyn = logistic_model.predict(X_test)

vis_metrics(y_test, pred_adasyn, "LogisticModelADASYN")
plt.show()
```

```
              precision    recall  f1-score   support   accuracy

           0       0.99      0.72      0.83       730       0.72
           1       0.13      0.84      0.23        37       0.84

    accuracy                           0.73       767   balanced accuracy: 0.78
   macro avg       0.56      0.78      0.53       767
```

```
weighted avg       0.95      0.73      0.80       767
```







We observe a good improvement over all the defined metrics when doing oversampling of the training dataset. Oversampling is shown to have a better performance compared to class weights with a considerable increase on the recall to 81% and an increase to the unbalanced accuracy to 76% from 70%. In this next part, we will use the over-sampled data on a neural network and on a random forset model since over-sampling proved to be the better technique in our case to combat the dataset distribution.

Neural Network

[51]:
```
nn = MLPClassifier(hidden_layer_sizes= (10, 5, 1))
nn.fit(X_train_adasyn, y_train_adasyn)
```

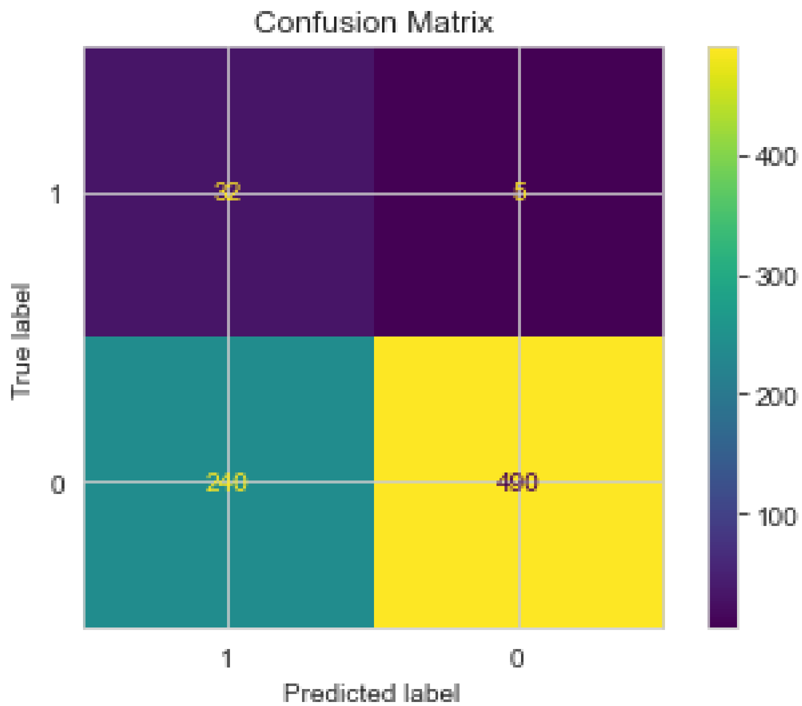
```
C:\Users\Charb\anaconda3\envs\ml\lib\site-
packages\sklearn\neural_network\_multilayer_perceptron.py:692:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
the optimization hasn't converged yet.
  warnings.warn(
```

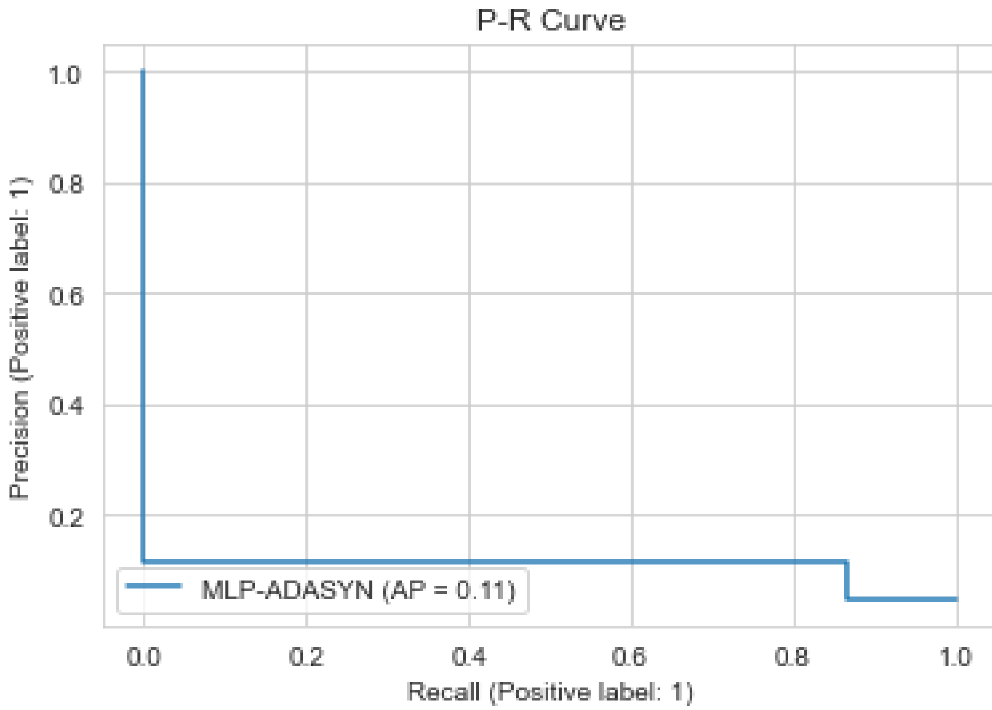
[51]:
```
MLPClassifier(hidden_layer_sizes=(10, 5, 1))
```

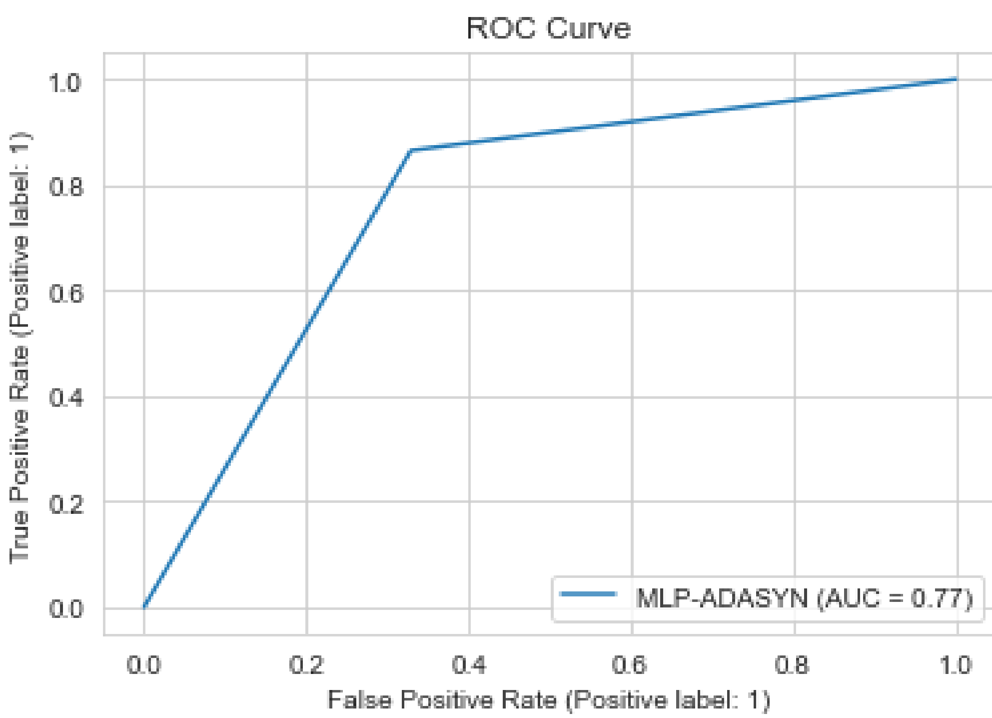
[52]:
```
pred_nn = nn.predict(X_test)
vis_metrics(y_test , pred_nn, "MLP-ADASYN")
```

```
              precision    recall  f1-score   support    accuracy
```

0	0.99	0.67	0.80	730	0.67
1	0.12	0.86	0.21	37	0.86
accuracy			0.68	767	balanced accuracy: 0.77
macro avg	0.55	0.77	0.50	767	
weighted avg	0.95	0.68	0.77	767	



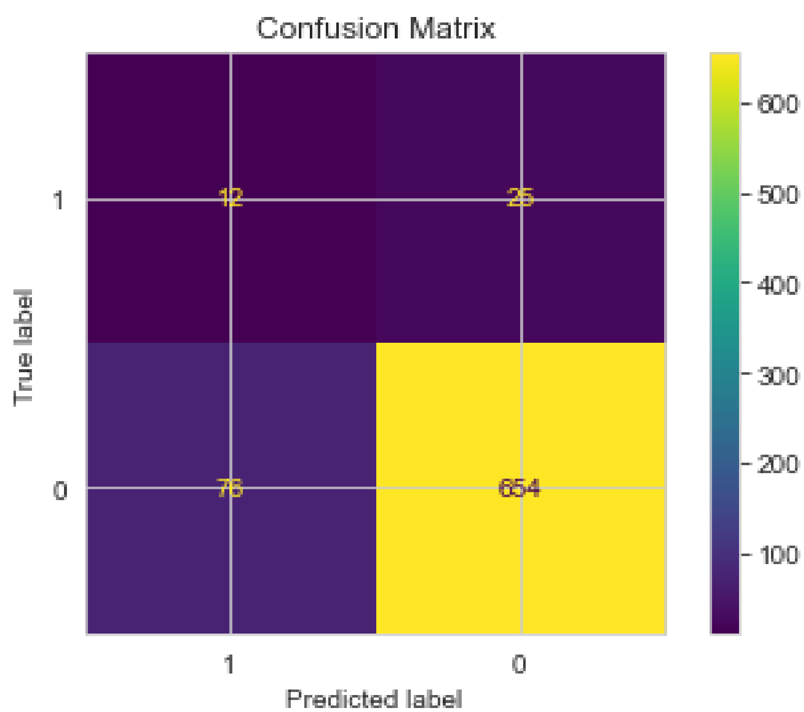

P-R Curve
1.0
0.8
0.6
0.4
0.2
Precision (Positive label: 1)
MLP-ADASYN (AP = 0.11)
0.0
0.2
0.4
0.6
0.8
1.0
Recall (Positive label: 1)

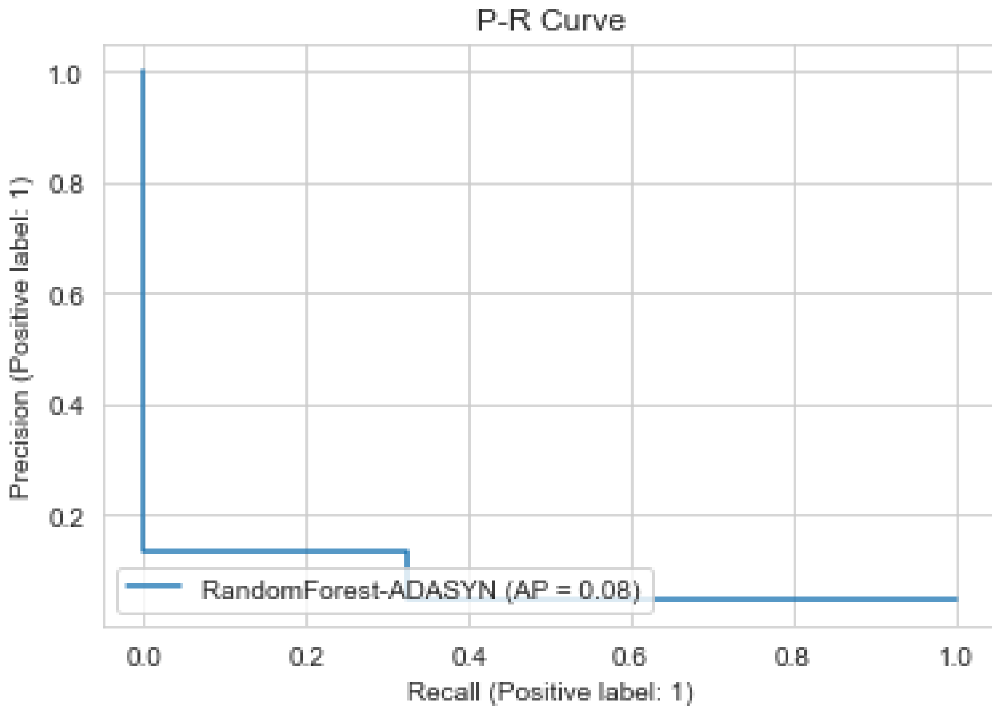

ROC Curve
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate (Positive label: 1)
MLP-ADASYN (AUC = 0.77)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (Positive label: 1)

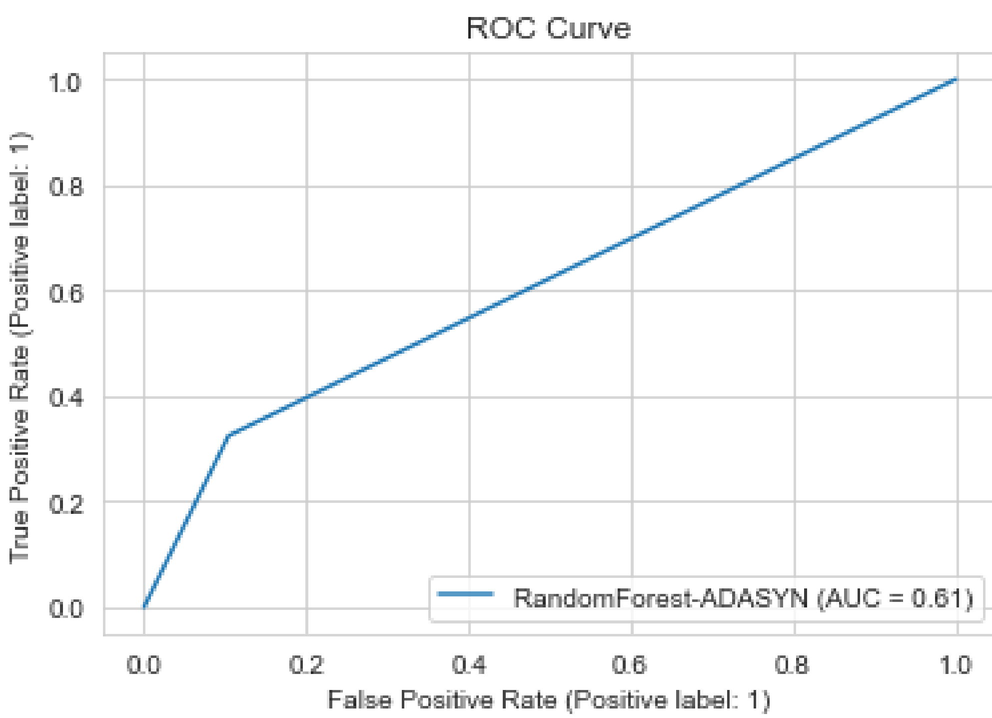
Random Forest

[48]:
```
rf_model = RandomForestClassifier()
rf_model.fit(X_train_adasyn, y_train_adasyn)

pred_rf = rf_model.predict(X_test)
vis_metrics(y_test, pred_rf, "RandomForest-ADASYN")
plt.show()
```

```
              precision    recall  f1-score   support    accuracy

           0       0.96      0.90      0.93       730        0.90
           1       0.14      0.32      0.19        37        0.32

    accuracy                           0.87       767    balanced accuracy: 0.61
   macro avg       0.55      0.61      0.56       767
weighted avg       0.92      0.87      0.89       767
```




P-R Curve
Precision (Positive label: 1)
Recall (Positive label: 1)
1.0
0.8
0.6
0.4
0.2
0.0
0.2
0.4
0.6
0.8
1.0
RandomForest-ADASYN (AP = 0.08)


ROC Curve
True Positive Rate (Positive label: 1)
False Positive Rate (Positive label: 1)
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
RandomForest-ADASYN (AUC = 0.61)

0.4.4 Model Evaluation

In this section, we evaluate all the three models implemented based on the defined metrics.

[53]:
```
print("Classification report for LOGISTIC REGRESSION - ADASYN")
print(classification_report(y_test, pred_adasyn))

print("Classification report for NEURAL NETWORK - ADASYN")
print(classification_report(y_test, pred_nn))

print("Classification report for RANDOM FOREST - ADASYN")
print(classification_report(y_test, pred_rf))
```

```
Classification report for LOGISTIC REGRESSION - ADASYN
              precision    recall  f1-score   support

           0       0.99      0.72      0.83       730
           1       0.13      0.84      0.23        37

    accuracy                           0.73       767
   macro avg       0.56      0.78      0.53       767
weighted avg       0.95      0.73      0.80       767

Classification report for NEURAL NETWORK - ADASYN
              precision    recall  f1-score   support

           0       0.99      0.67      0.80       730
           1       0.12      0.86      0.21        37

    accuracy                           0.68       767
   macro avg       0.55      0.77      0.50       767
weighted avg       0.95      0.68      0.77       767

Classification report for RANDOM FOREST - ADASYN
              precision    recall  f1-score   support

           0       0.96      0.90      0.93       730
           1       0.14      0.32      0.19        37

    accuracy                           0.87       767
   macro avg       0.55      0.61      0.56       767
weighted avg       0.92      0.87      0.89       767
```

[54]:
```
fpr_lr, tpr_lr, _ = roc_curve(y_true= y_test, y_score= pred_adasyn)
fpr_nn, tpr_nn, _ = roc_curve(y_true= y_test, y_score= pred_nn)
fpr_rf, tpr_rf, _ = roc_curve(y_true= y_test, y_score= pred_rf)
```

```
print(f"False Positive Rate/True Positive Rate for LOGISTIC REGRESSION - ADASYN:
 ↪ {fpr_lr[1]:.2f} - {tpr_lr[1]:.2f}")
print(f"False Positive Rate/True Positive Rate for NEURAL NETWORK - ADASYN:␣
 ↪{fpr_nn[1]:.2f} - {tpr_nn[1]:.2f}")
print(f"False Positive Rate/True Positive Rate for RANDOM FOREST - ADASYN:␣
 ↪{fpr_rf[1]:.2f} - {tpr_rf[1]:.2f}")
```

```
False Positive Rate/True Positive Rate for LOGISTIC REGRESSION - ADASYN: 0.28 -
0.84
False Positive Rate/True Positive Rate for NEURAL NETWORK - ADASYN: 0.33 - 0.86
False Positive Rate/True Positive Rate for RANDOM FOREST - ADASYN: 0.10 - 0.32
```

From the following data and the plots shown previously, we could possibly deploy the neural network model having the highest true positives rate. There are some other techniques we could implement to have a better assessment for our model however, due to the time limitations for this study we will suffise with the performed study.