Stroke Prediction Project

April 27, 2021

0.0.1 Table of Contents

0.0.2 Intro

This data was aquired from fedesoriano on kaggle. The goal of this project is to predict stroke in a patient. The variable directory is as follows:
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

0.0.3 Import Packages

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings("ignore")
```

0.0.4 Read in Data

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

[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

       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

   stroke
0       1
1       1
2       1
3       1
4       1
```

After taking a deeper look at the data, we see that there are some missing values for bmi.

[3]:
```
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
```

0.0.5 Missing Values

I wanted to see how many missing values we had, as well as the percentage of missing values.

[4]:
```
stroke.isnull().sum()
```

[4]:
```
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
```

[5]:
```
round(stroke.isnull().sum() / len(stroke["id"]) * 100, 2)
```

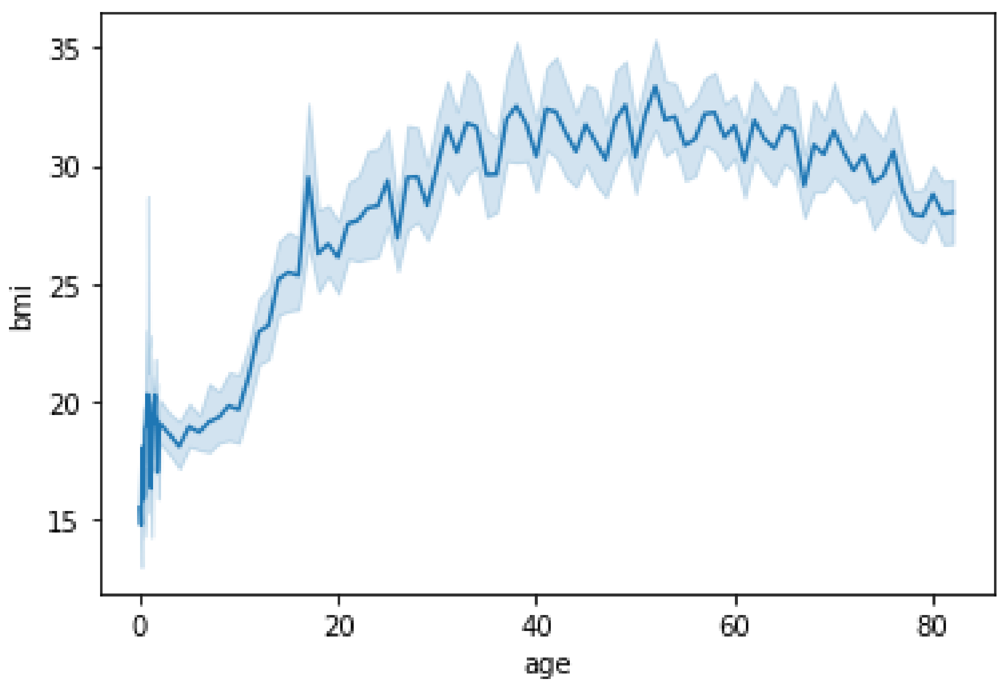
[5]:
```
id                   0.00
gender               0.00
age                  0.00
```

```
hypertension         0.00
heart_disease        0.00
ever_married         0.00
work_type            0.00
Residence_type       0.00
avg_glucose_level    0.00
bmi                  3.93
smoking_status       0.00
stroke               0.00
dtype: float64
```

I chose to impute my data based on age, since children tend to have a lower bmi. We can see this in the plot below.

[6]:
```
sns.lineplot(x='age', y='bmi', data=stroke)
```

[6]: <AxesSubplot:xlabel='age', ylabel='bmi'>



I made three age groups to compare the bmis. The 18-60 and 60+ have similar bmis, so I will use the mean bmi for each group.

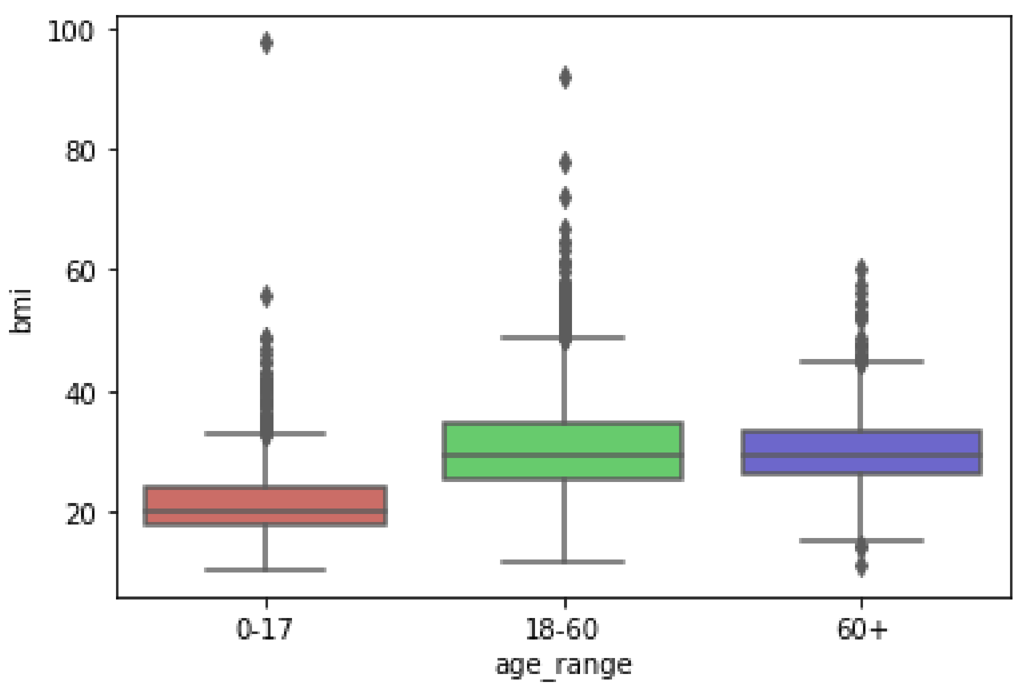
[7]:
```
bins = [0,18, 60, 90]
labels = ['0-17', '18-60', '60+']
stroke['age_range'] = pd.cut(stroke.age, bins, labels = labels,include_lowest =␣
↪True)
```

[8]:
```
stroke['age_range'][:10]
```

[8]:
```
0      60+
1      60+
2      60+
3    18-60
4      60+
5      60+
6      60+
7      60+
8    18-60
9      60+
Name: age_range, dtype: category
Categories (3, object): ['0-17' < '18-60' < '60+']
```

[9]:
```
sns.boxplot(x='age_range', y='bmi', data=stroke, palette='hls')
```

[9]:
```
<AxesSubplot:xlabel='age_range', ylabel='bmi'>
```



[10]:
```
age_groups = stroke.groupby(stroke['age_range'])
age_groups.mean()
```

[10]:
```
                     id       age  hypertension  heart_disease  \
age_range
0-17       36326.597162  9.179039      0.001092       0.001092
```

```
18-60      36666.172664  41.258131      0.074394       0.022491
60+        36323.394172  71.506135      0.216258       0.161043

           avg_glucose_level        bmi    stroke
age_range
0-17               94.768395  21.714302  0.002183
18-60             102.581249  30.763926  0.024221
60+               122.045222  29.873377  0.135736
```

[11]:
```
def bmi_approx(cols):
    bmi = cols[0]
    age_range = cols[1]

    if pd.isnull(bmi):
        if age_range == "0-17":
            return 22
        else:
            return 30

    else:
        return bmi
```

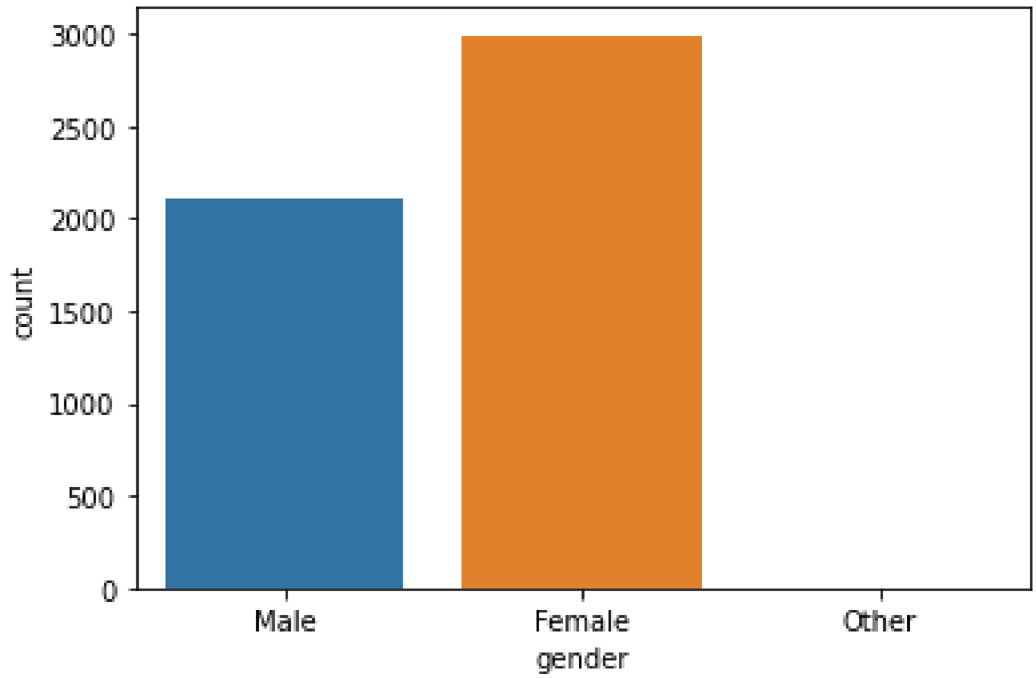
[12]:
```
stroke['bmi']= stroke[['bmi', 'age_range']].apply(bmi_approx, axis=1)
stroke.isnull().sum()
```

[12]:
```
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
age_range            0
dtype: int64
```

0.0.6 EDA

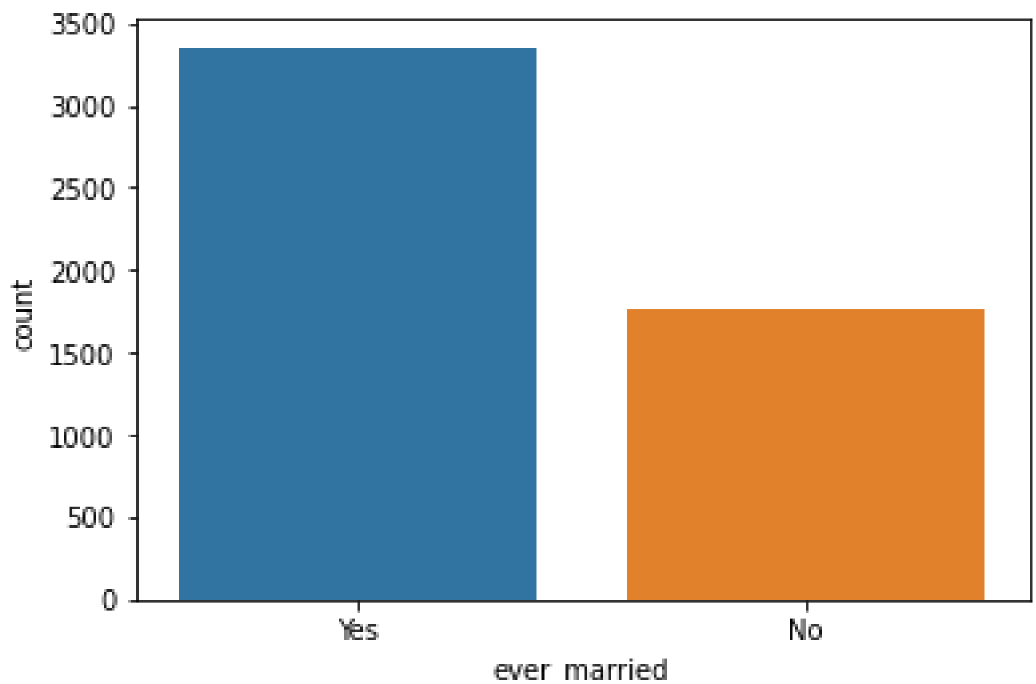
[13]:
```
sns.countplot(x = 'gender', data = stroke)
```

[13]:
```
<AxesSubplot:xlabel='gender', ylabel='count'>
```



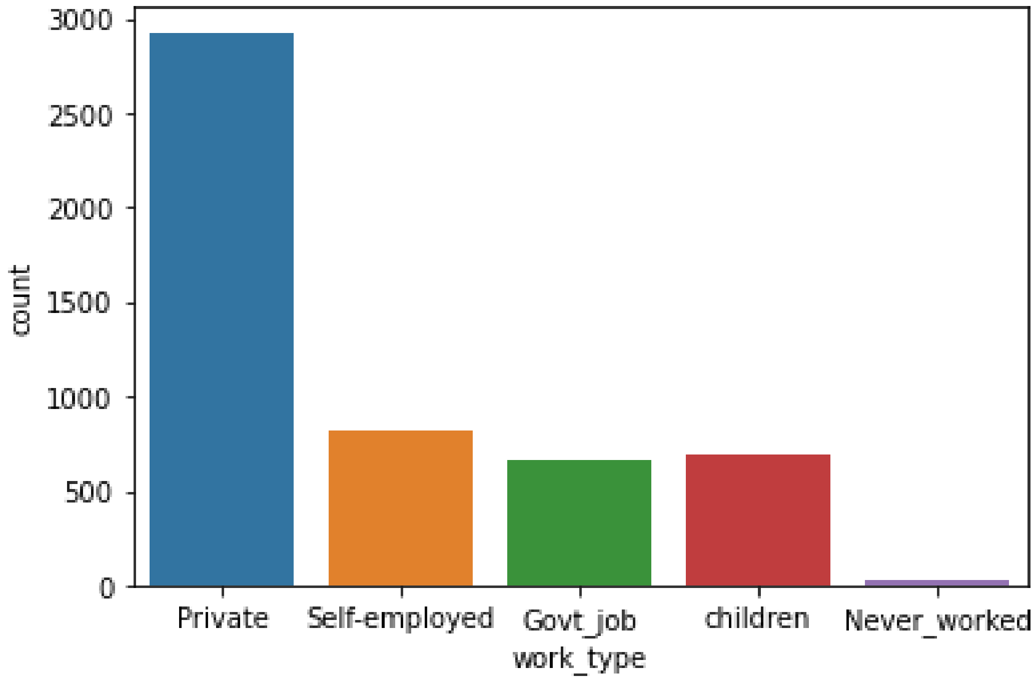
[14]:
```
sns.countplot(x = 'ever_married', data = stroke)
```

[14]: <AxesSubplot:xlabel='ever_married', ylabel='count'>



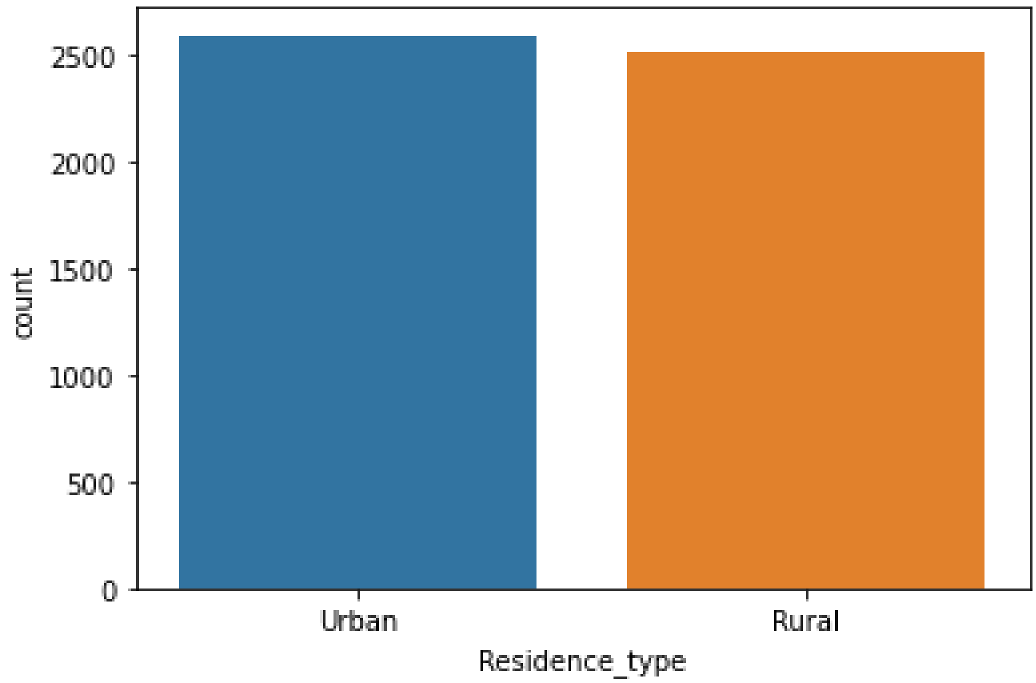
[15]:
```
sns.countplot(x = 'work_type', data = stroke)
```

[15]: <AxesSubplot:xlabel='work_type', ylabel='count'>



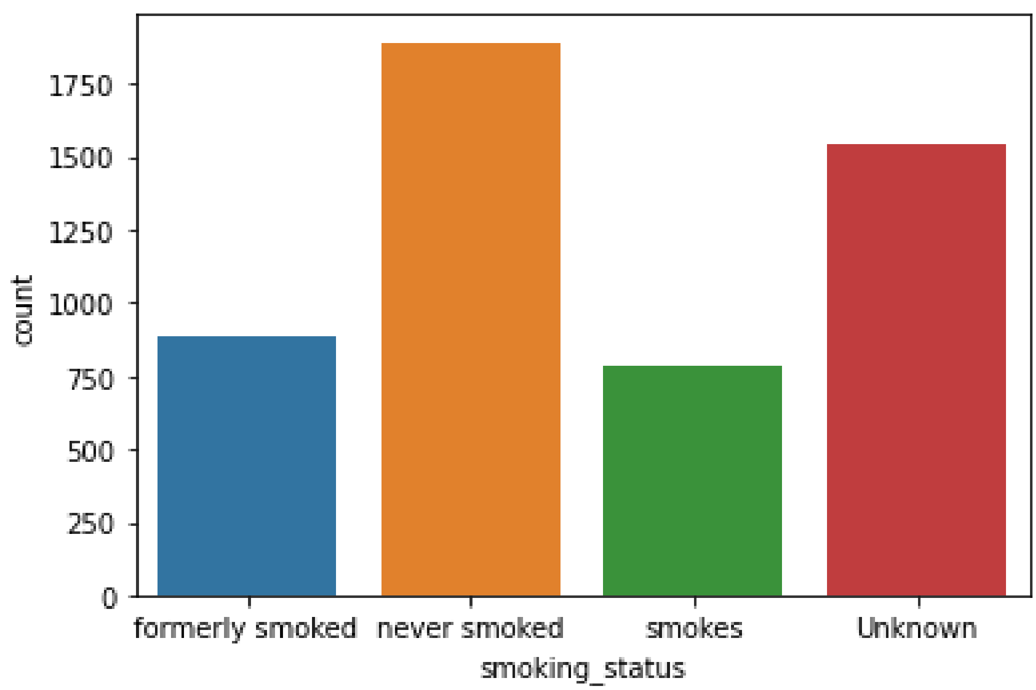
[16]:
```
sns.countplot(x = 'Residence_type', data = stroke)
```

[16]: <AxesSubplot:xlabel='Residence_type', ylabel='count'>



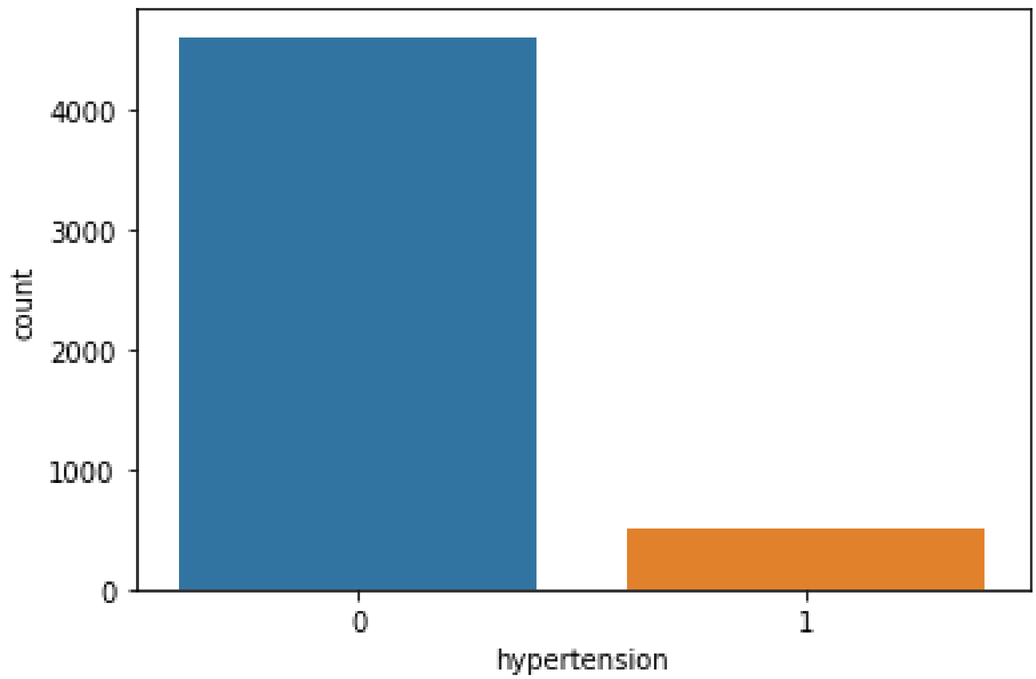
[17]:
```
sns.countplot(x = 'smoking_status', data = stroke)
```

[17]: <AxesSubplot:xlabel='smoking_status', ylabel='count'>



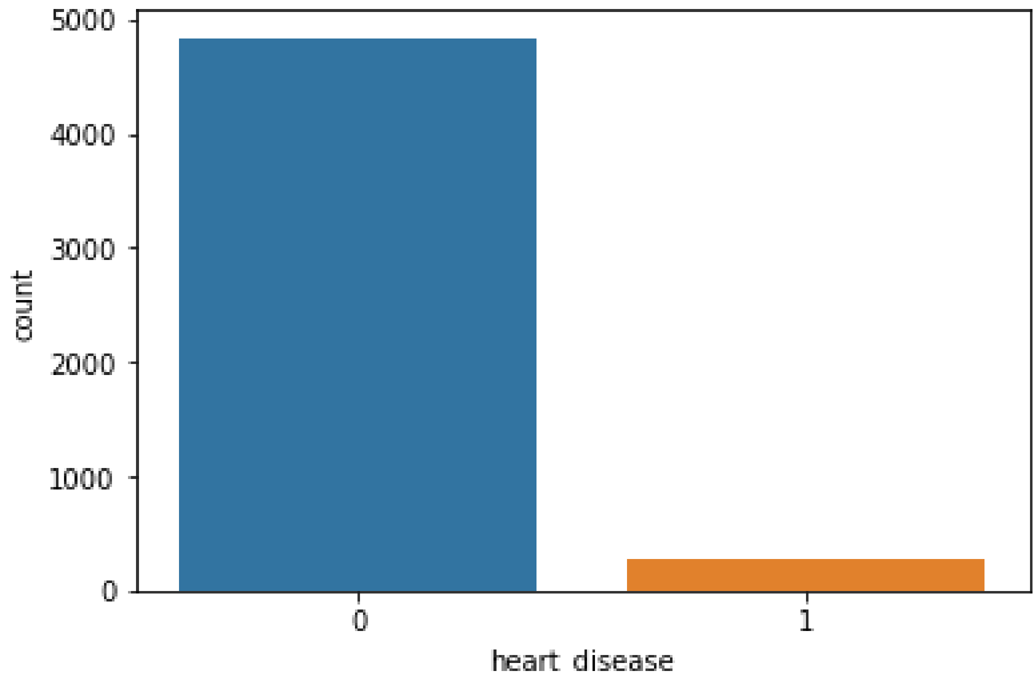
[18]:
```
sns.countplot(x = 'hypertension', data = stroke)
```

[18]: <AxesSubplot:xlabel='hypertension', ylabel='count'>



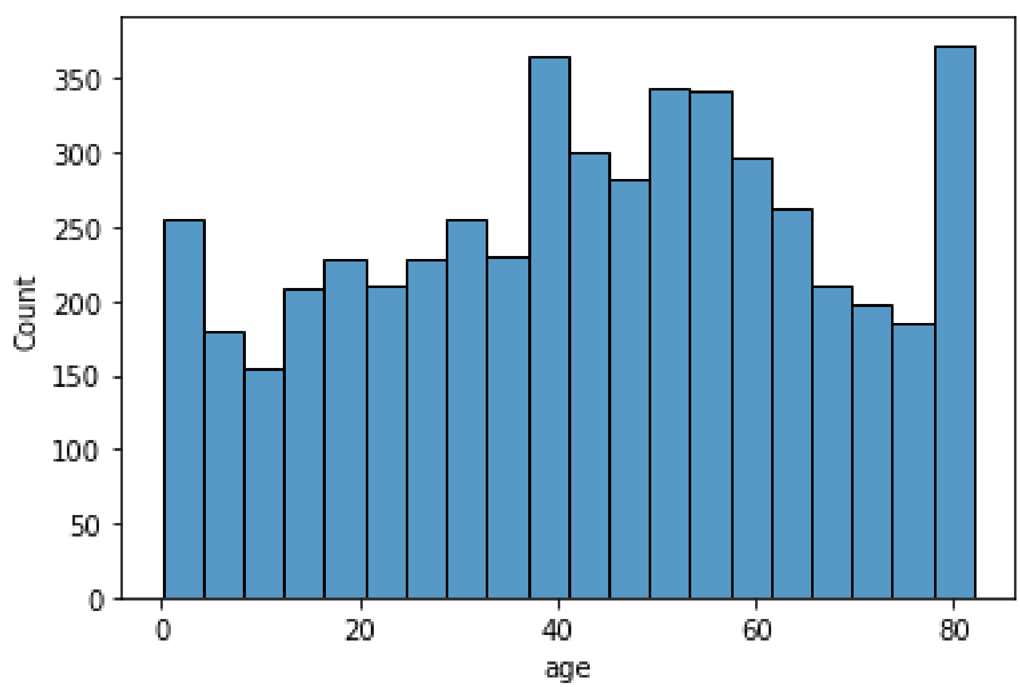
[19]:
```
sns.countplot(x = 'heart_disease', data = stroke)
```

[19]: <AxesSubplot:xlabel='heart_disease', ylabel='count'>



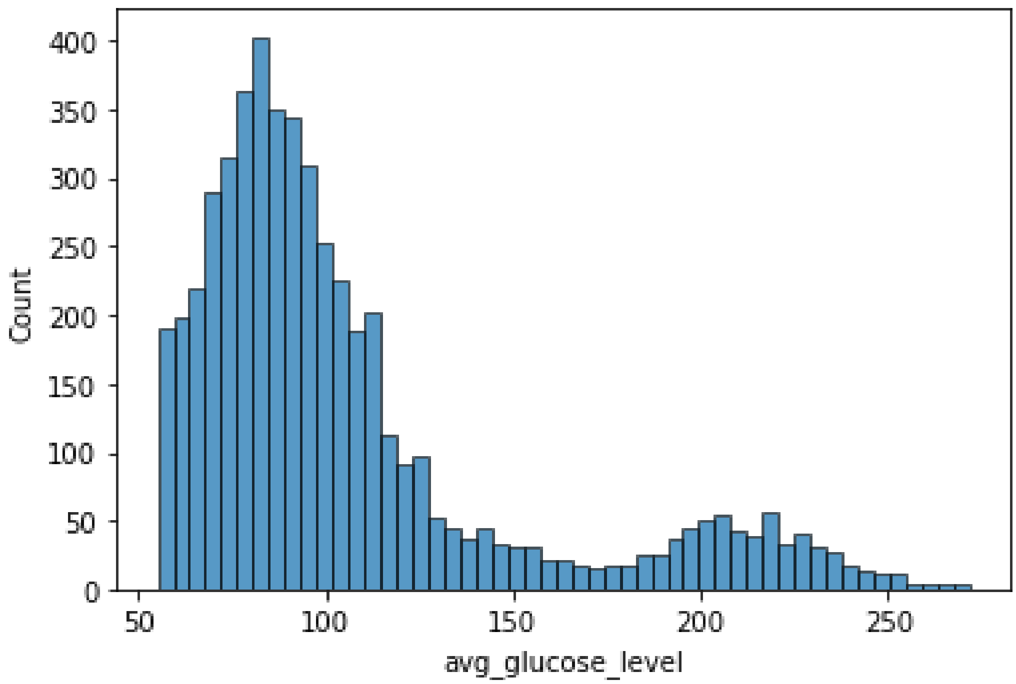

```
[20]: sns.histplot(x = 'age', data = stroke)
```

[20]: <AxesSubplot:xlabel='age', ylabel='Count'>



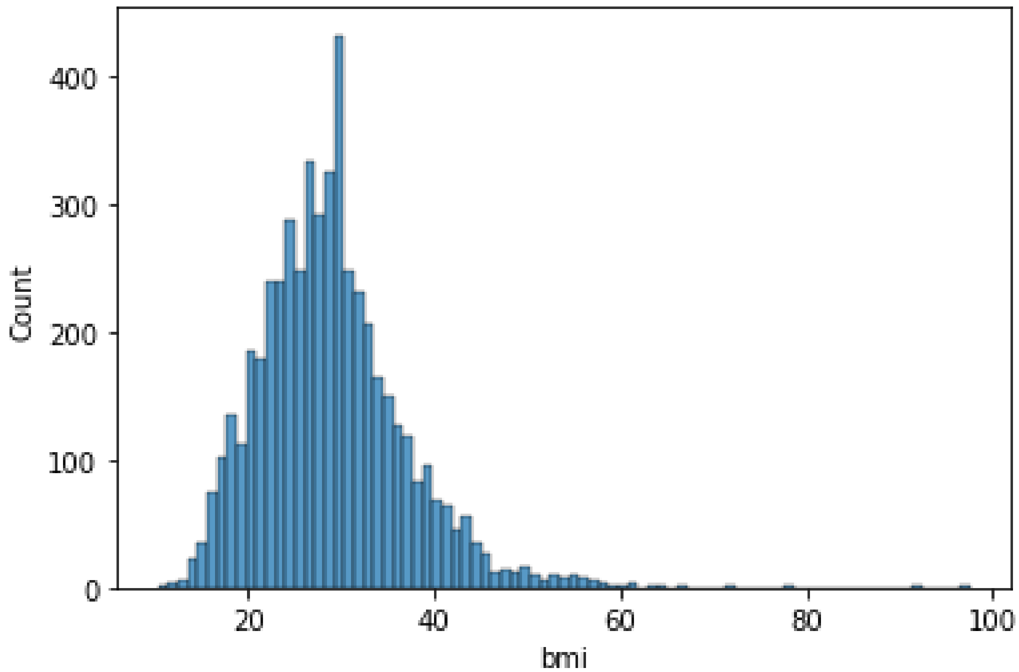
[21]:
```
sns.histplot(x = 'avg_glucose_level', data = stroke)
```

[21]: <AxesSubplot:xlabel='avg_glucose_level', ylabel='Count'>



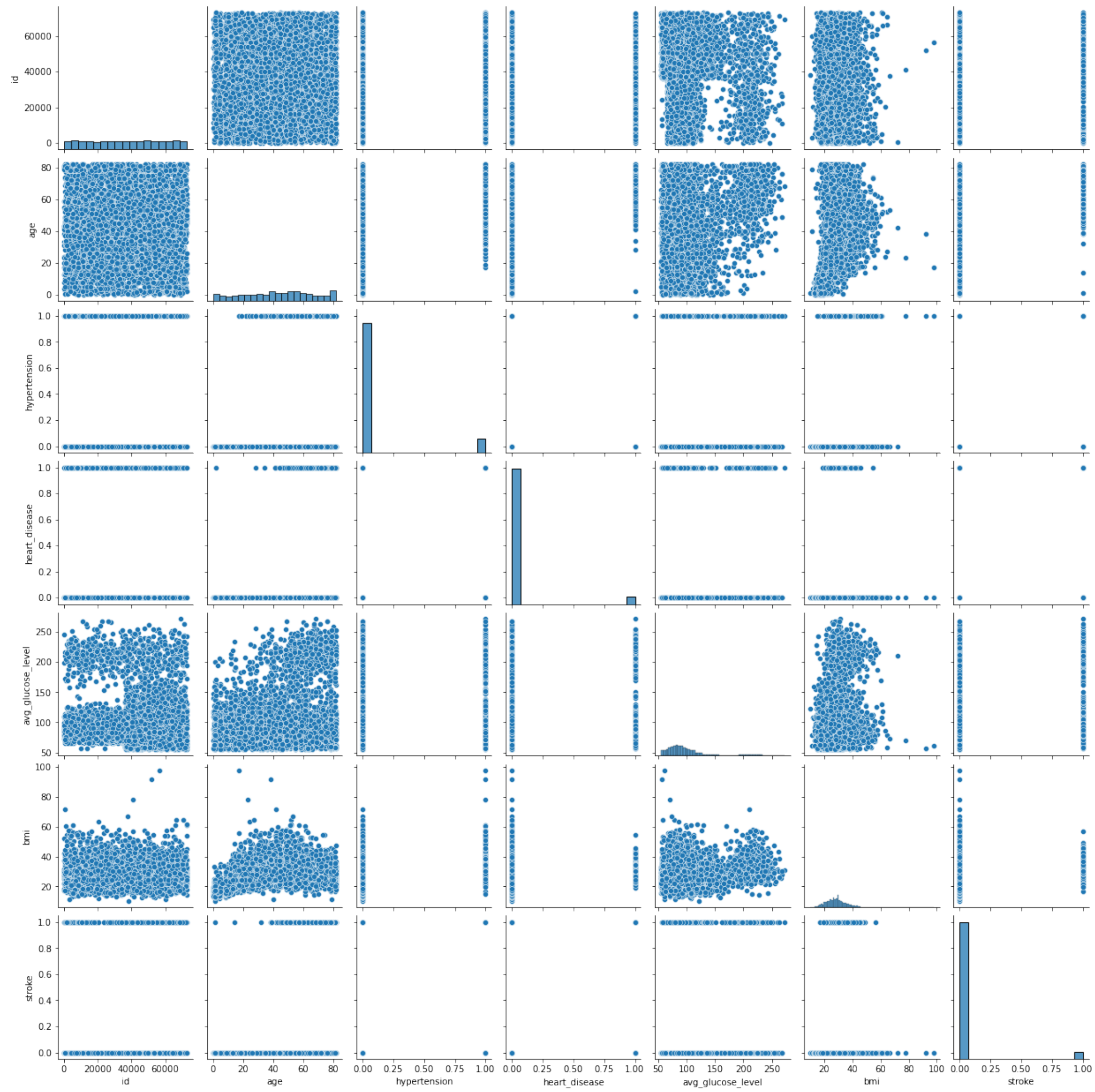
[22]:
```
sns.histplot(x = 'bmi', data = stroke)
```

[22]: <AxesSubplot:xlabel='bmi', ylabel='Count'>



[23]:
```
fig = plt.figure(figsize=(10,10))
sns.pairplot(stroke)
plt.show()
```

```
<Figure size 720x720 with 0 Axes>
```



0.0.7 Preprocessing

We are going to create dummy variables for the categorical variables.

[24]:
```
stroke.drop(stroke.index[3116], inplace= True)
```

[25]:
```
stroke = stroke.reset_index(drop=True)
```

[26]:
```
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()

gender_cat = stroke['gender']
```

```
gender_encoded = label_encoder.fit_transform(gender_cat)
gender_encoded[0:5]
```

[26]:
```
array([1, 0, 1, 0, 0])
```

[27]:
```
# 1 = male / 0 = female
gender_DF = pd.DataFrame(gender_encoded, columns=['male_gender'])
gender_DF.head()
```

[27]:

	male_gender
0	1
1	0
2	1
3	0
4	0

[28]:
```
married_cat = stroke['ever_married']
married_encoded = label_encoder.fit_transform(married_cat)
married_encoded[0:5]
```

[28]:
```
array([1, 1, 1, 1, 1])
```

[29]:
```
# 1 = yes / 0 = no
married_DF = pd.DataFrame(married_encoded, columns=['married'])
married_DF.head()
```

[29]:

	married
0	1
1	1
2	1
3	1
4	1

[30]:
```
res_cat = stroke['Residence_type']
res_encoded = label_encoder.fit_transform(res_cat)
res_encoded[0:5]
```

[30]:
```
array([1, 0, 0, 1, 0])
```

[31]:
```
# 1 = urban / 0 = rural
res_DF = pd.DataFrame(res_encoded, columns=['residence_urban'])
res_DF.head()
```

[31]:

	residence_urban
0	1
1	0
2	0

```
3                 1
4                 0
```

[32]:
```
work_cat = stroke['work_type']
work_encoded = label_encoder.fit_transform(work_cat)
work_encoded[0:250]
```

[32]:
```
array([2, 3, 2, 2, 3, 2, 2, 2, 2, 2, 2, 0, 2, 2, 2, 3, 2, 2, 2, 0, 0, 3,
       3, 2, 2, 3, 2, 2, 3, 2, 2, 2, 3, 3, 0, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       0, 2, 3, 2, 3, 2, 2, 2, 2, 3, 0, 2, 2, 2, 3, 0, 2, 2, 3, 2, 2, 2,
       2, 2, 2, 3, 0, 2, 0, 2, 2, 3, 2, 2, 2, 3, 2, 3, 2, 3, 2, 2, 2, 2,
       2, 2, 2, 2, 3, 3, 2, 2, 3, 2, 0, 0, 0, 0, 2, 3, 0, 2, 2, 3, 2, 0,
       2, 2, 3, 2, 0, 0, 3, 2, 3, 2, 2, 2, 2, 2, 2, 0, 3, 2, 0, 0, 2, 2,
       2, 2, 3, 0, 2, 2, 3, 2, 0, 2, 2, 3, 2, 2, 3, 2, 0, 2, 2, 2, 3, 3,
       3, 2, 2, 2, 3, 3, 2, 2, 4, 2, 3, 3, 0, 2, 0, 3, 3, 3, 2, 3, 3, 3,
       2, 3, 0, 2, 2, 2, 2, 2, 2, 2, 3, 0, 2, 2, 2, 2, 3, 2, 2, 2, 2, 2,
       2, 3, 2, 2, 3, 3, 0, 2, 2, 3, 3, 0, 2, 0, 2, 2, 3, 2, 3, 2, 3, 0,
       2, 2, 0, 0, 2, 2, 2, 3, 3, 2, 3, 2, 3, 3, 3, 2, 2, 3, 2, 2, 2, 2,
       2, 2, 2, 4, 3, 3, 2, 4])
```

[33]:
```
stroke['work_type'].unique()
```

[33]:
```
array(['Private', 'Self-employed', 'Govt_job', 'children', 'Never_worked'],
      dtype=object)
```

[34]:
```
stroke[stroke.isna().any(axis=1)]
```

[34]:
```
Empty DataFrame
Columns: [id, gender, age, hypertension, heart_disease, ever_married, work_type,
Residence_type, avg_glucose_level, bmi, smoking_status, stroke, age_range]
Index: []
```

[35]:
```
from sklearn.preprocessing import OneHotEncoder

binary_encoder = OneHotEncoder(categories='auto')
work_1hot = binary_encoder.fit_transform(work_encoded.reshape(-1,1))
work_1hot_mat = work_1hot.toarray()
work_DF = pd.DataFrame(work_1hot_mat,
            columns = ['Govt_job', 'Never_worked',
                    'Private_job', 'Self-employed','children_job'])
work_DF.head()
```

[35]:

	Govt_job	Never_worked	Private_job	Self-employed	children_job
0	0.0	0.0	1.0	0.0	0.0
1	0.0	0.0	0.0	1.0	0.0
2	0.0	0.0	1.0	0.0	0.0
3	0.0	0.0	1.0	0.0	0.0

```
4       0.0           0.0          0.0            1.0           0.0
```

```
[36]: smoke_cat = stroke['smoking_status']
smoke_encoded = label_encoder.fit_transform(smoke_cat)
smoke_encoded[0:50]
```

```
[36]: array([1, 2, 2, 3, 2, 1, 2, 2, 0, 0, 2, 3, 3, 0, 2, 2, 3, 3, 2, 0, 3, 2,
       2, 0, 1, 2, 1, 0, 3, 1, 3, 0, 2, 1, 2, 1, 1, 1, 0, 2, 1, 2, 3, 1,
       3, 2, 0, 1, 2, 3])
```

```
[37]: stroke['smoking_status'].unique()
```

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

```
[38]: smoke_1hot = binary_encoder.fit_transform(smoke_encoded.reshape(-1,1))
smoke_1hot_mat = smoke_1hot.toarray()
smoke_DF = pd.DataFrame(smoke_1hot_mat,
            columns = ['Unknown_smoke', 'formerly_smoked',
                    'never_smoked', 'smokes'])
smoke_DF.head()
```

[38]:

	Unknown_smoke	formerly_smoked	never_smoked	smokes
0	0.0	1.0	0.0	0.0
1	0.0	0.0	1.0	0.0
2	0.0	0.0	1.0	0.0
3	0.0	0.0	0.0	1.0
4	0.0	0.0	1.0	0.0

```
[39]: stroke.drop(['gender', 'ever_married', 'work_type',
              'Residence_type', 'smoking_status',
              'age_range', 'id'], axis=1, inplace=True)
stroke.head()
```

[39]:

	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	30.0	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

```
[40]: stroke_dmy = pd.concat([stroke, gender_DF, married_DF,
                       res_DF, work_DF, smoke_DF],
                       axis=1, verify_integrity=True)
stroke_dmy[0:5]
```

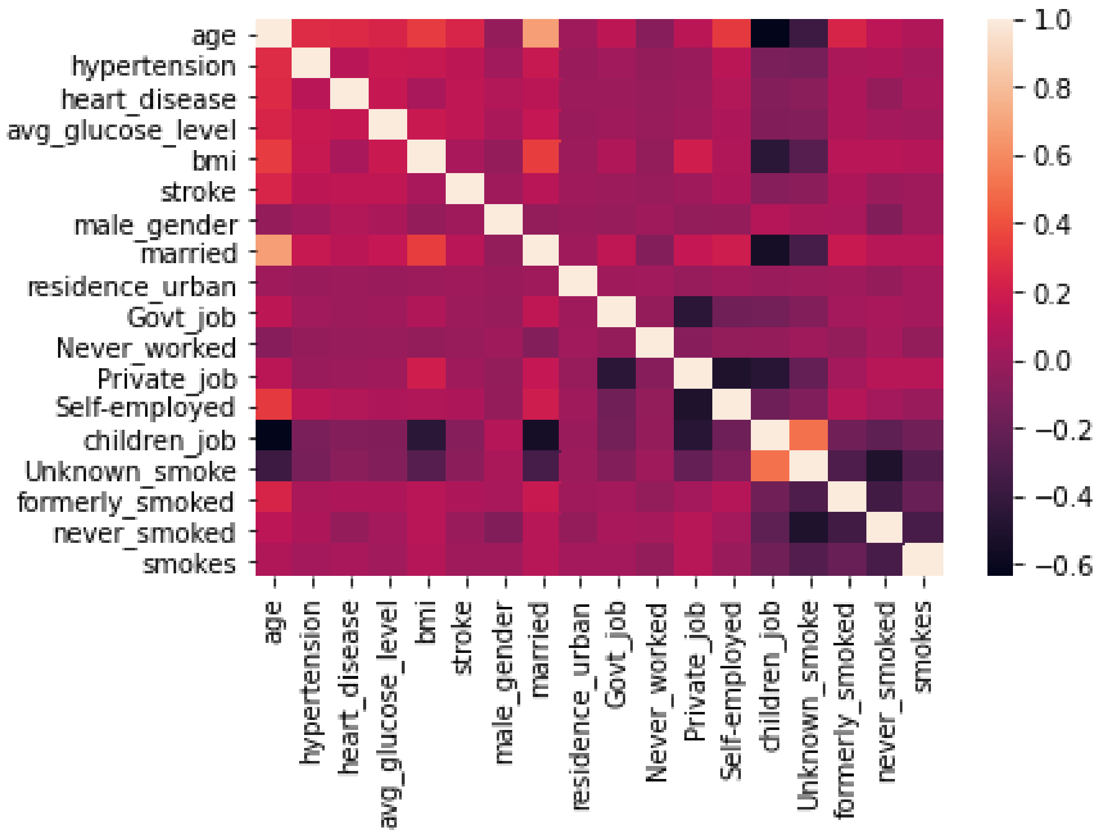
[40]:
```
    age  hypertension  heart_disease  avg_glucose_level   bmi  stroke  \
0  67.0             0              1             228.69  36.6       1
1  61.0             0              0             202.21  30.0       1
2  80.0             0              1             105.92  32.5       1
3  49.0             0              0             171.23  34.4       1
4  79.0             1              0             174.12  24.0       1

   male_gender  married  residence_urban  Govt_job  Never_worked  Private_job  \
0            1        1                1       0.0           0.0          1.0
1            0        1                0       0.0           0.0          0.0
2            1        1                0       0.0           0.0          1.0
3            0        1                1       0.0           0.0          1.0
4            0        1                0       0.0           0.0          0.0

   Self-employed  children_job  Unknown_smoke  formerly_smoked  never_smoked  \
0            0.0           0.0            0.0              1.0           0.0
1            1.0           0.0            0.0              0.0           1.0
2            0.0           0.0            0.0              0.0           1.0
3            0.0           0.0            0.0              0.0           0.0
4            1.0           0.0            0.0              0.0           1.0

   smokes
0     0.0
1     0.0
2     0.0
3     1.0
4     0.0
```

[41]:
```
stroke_dmy[stroke_dmy.isna().any(axis=1)]
```

[41]:
```
Empty DataFrame
Columns: [age, hypertension, heart_disease, avg_glucose_level, bmi, stroke,
male_gender, married, residence_urban, Govt_job, Never_worked, Private_job,
Self-employed, children_job, Unknown_smoke, formerly_smoked, never_smoked,
smokes]
Index: []
```

[42]:
```
sns.heatmap(stroke_dmy.corr())
```

[42]:
```
<AxesSubplot:>
```



0.0.8 Train/ Test Split

[43]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    stroke_dmy.drop('stroke', axis=1),
    stroke_dmy['stroke'], test_size=0.2)
```

0.0.9 Feature Scaling

[44]:
```
from sklearn.preprocessing import StandardScaler

sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

When we look at the value counts for stroke we can see that the data is imbalanced. We will apply SMOTE to combat that.

[45]:
```
stroke['stroke'].value_counts()
```

[45]:
```
0    4860
1     249
Name: stroke, dtype: int64
```

[46]:
```
from imblearn.over_sampling import SMOTE
```

[47]:
```
sm = SMOTE(random_state=4)
X_train_res, y_train_res = sm.fit_resample(X_train, y_train.ravel())
```

[ ]:
```

```

0.0.10 Model Selection

For this section will be using code from Siddhesh Sawant.I was interested in running multiple models at once using a for loop.

[48]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.naive_bayes import BernoulliNB
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
```

[49]:
```
from sklearn.metrics import accuracy_score, confusion_matrix, roc_auc_score,␣
↪ConfusionMatrixDisplay, precision_score, recall_score, f1_score,␣
↪classification_report, roc_curve, plot_roc_curve, auc,␣
↪precision_recall_curve, plot_precision_recall_curve, average_precision_score
from sklearn.model_selection import cross_val_score
```

[50]:
```
models = []
models.append(['Logistic Regreesion', LogisticRegression(random_state=0)])
models.append(['SVM', SVC(random_state=0)])
models.append(['KNeighbors', KNeighborsClassifier()])
models.append(['GaussianNB', GaussianNB()])
models.append(['BernoulliNB', BernoulliNB()])
models.append(['Decision Tree', DecisionTreeClassifier(random_state=0)])
models.append(['Random Forest', RandomForestClassifier(random_state=0)])
models.append(['XGBoost', XGBClassifier(eval_metric= 'error')])

lst_1= []

for m in range(len(models)):
```

```
    lst_2= []
    model = models[m][1]
    model.fit(X_train_res, y_train_res)
    y_pred = model.predict(X_test)
    cm = confusion_matrix(y_test, y_pred)  #Confusion Matrix
    accuracies = cross_val_score(estimator = model, X = X_train_res, y = y_train_res, cv = 10)   #K-Fold Validation
    roc = roc_auc_score(y_test, y_pred)  #ROC AUC Score
    precision = precision_score(y_test, y_pred)  #Precision Score
    recall = recall_score(y_test, y_pred)  #Recall Score
    f1 = f1_score(y_test, y_pred)  #F1 Score
    print(models[m][0],':')
    print(cm)
    print('Accuracy Score: ',accuracy_score(y_test, y_pred))
    print('')
    print("K-Fold Validation Mean Accuracy: {:.2f} %".format(accuracies.mean()*100))
    print('')
    print("Standard Deviation: {:.2f} %".format(accuracies.std()*100))
    print('')
    print('ROC AUC Score: {:.2f}'.format(roc))
    print('')
    print('Precision: {:.2f}'.format(precision))
    print('')
    print('Recall: {:.2f}'.format(recall))
    print('')
    print('F1: {:.2f}'.format(f1))
    print('-----------------------------------')
    print('')
    lst_2.append(models[m][0])
    lst_2.append((accuracy_score(y_test, y_pred))*100)
    lst_2.append(accuracies.mean()*100)
    lst_2.append(accuracies.std()*100)
    lst_2.append(roc)
    lst_2.append(precision)
    lst_2.append(recall)
    lst_2.append(f1)
    lst_1.append(lst_2)
```

```
Logistic Regreesion :
[[745 231]
 [ 12  34]]
Accuracy Score:  0.7622309197651663

K-Fold Validation Mean Accuracy: 79.15 %

Standard Deviation: 1.41 %
```

```
ROC AUC Score: 0.75

Precision: 0.13

Recall: 0.74

F1: 0.22
-----------------------------------

SVM :
[[805 171]
 [ 25  21]]
Accuracy Score:  0.8082191780821918

K-Fold Validation Mean Accuracy: 88.13 %

Standard Deviation: 1.51 %

ROC AUC Score: 0.64

Precision: 0.11

Recall: 0.46

F1: 0.18
-----------------------------------

KNeighbors :
[[827 149]
 [ 34  12]]
Accuracy Score:  0.8209393346379648

K-Fold Validation Mean Accuracy: 91.32 %

Standard Deviation: 0.80 %

ROC AUC Score: 0.55

Precision: 0.07

Recall: 0.26

F1: 0.12
-----------------------------------

GaussianNB :
[[290 686]
```

```
 [  0  46]]
Accuracy Score:  0.3287671232876712

K-Fold Validation Mean Accuracy: 64.28 %

Standard Deviation: 1.06 %

ROC AUC Score: 0.65

Precision: 0.06

Recall: 1.00

F1: 0.12
-----------------------------------

BernoulliNB :
[[593 383]
 [  8  38]]
Accuracy Score:  0.6174168297455969

K-Fold Validation Mean Accuracy: 71.81 %

Standard Deviation: 1.03 %

ROC AUC Score: 0.72

Precision: 0.09

Recall: 0.83

F1: 0.16
-----------------------------------

Decision Tree :
[[879  97]
 [ 38   8]]
Accuracy Score:  0.8679060665362035

K-Fold Validation Mean Accuracy: 90.42 %

Standard Deviation: 3.87 %

ROC AUC Score: 0.54

Precision: 0.08

Recall: 0.17
```

```
F1: 0.11
-----------------------------------

Random Forest :
[[931  45]
 [ 42   4]]
Accuracy Score:  0.9148727984344422

K-Fold Validation Mean Accuracy: 96.00 %

Standard Deviation: 2.15 %

ROC AUC Score: 0.52

Precision: 0.08

Recall: 0.09

F1: 0.08
-----------------------------------

XGBoost :
[[955  21]
 [ 44   2]]
Accuracy Score:  0.9363992172211351

K-Fold Validation Mean Accuracy: 95.48 %

Standard Deviation: 6.57 %

ROC AUC Score: 0.51

Precision: 0.09

Recall: 0.04

F1: 0.06
-----------------------------------
```

0.0.11 Model Tuning

[51]:
```python
from sklearn.model_selection import GridSearchCV
```

[52]:
```
grid_models = [(LogisticRegression(),[{'C':[0.25,0.5,0.75,1],'random_state':
↪[0]}]),
               (KNeighborsClassifier(),[{'n_neighbors':[5,7,8,10], 'metric':␣
↪['euclidean', 'manhattan', 'chebyshev', 'minkowski']}]),
               (SVC(),[{'C':[0.25,0.5,0.75,1],'kernel':['linear',␣
↪'rbf'],'random_state':[0]}]),
               (GaussianNB(),[{'var_smoothing': [1e-09]}]),
               (BernoulliNB(), [{'alpha': [0.25, 0.5, 1]}]),
               (DecisionTreeClassifier(),[{'criterion':
↪['gini','entropy'],'random_state':[0]}]),
               (RandomForestClassifier(),[{'n_estimators':
↪[100,150,200],'criterion':['gini','entropy'],'random_state':[0]}]),
              (XGBClassifier(), [{'learning_rate': [0.01, 0.05, 0.1],␣
↪'eval_metric': ['error']}])]
```

[53]:
```
for i,j in grid_models:
    grid = GridSearchCV(estimator=i,param_grid = j, scoring = 'accuracy',cv =␣
↪10)
    grid.fit(X_train_res, y_train_res)
    best_accuracy = grid.best_score_
    best_param = grid.best_params_
    print('{}:\nBest Accuracy : {:.2f}%'.format(i,best_accuracy*100))
    print('Best Parameters : ',best_param)
    print('')
    print('----------------')
    print('')
```

```
LogisticRegression():
Best Accuracy : 79.22%
Best Parameters :  {'C': 0.25, 'random_state': 0}

----------------

KNeighborsClassifier():
Best Accuracy : 92.47%
Best Parameters :  {'metric': 'manhattan', 'n_neighbors': 5}

----------------

SVC():
Best Accuracy : 88.13%
Best Parameters :  {'C': 1, 'kernel': 'rbf', 'random_state': 0}

----------------

GaussianNB():
Best Accuracy : 64.28%
```

```
Best Parameters :  {'var_smoothing': 1e-09}

----------------

BernoulliNB():
Best Accuracy : 71.81%
Best Parameters :  {'alpha': 0.25}

----------------

DecisionTreeClassifier():
Best Accuracy : 90.73%
Best Parameters :  {'criterion': 'entropy', 'random_state': 0}

----------------

RandomForestClassifier():
Best Accuracy : 96.16%
Best Parameters :  {'criterion': 'entropy', 'n_estimators': 150, 'random_state':
0}

----------------

XGBClassifier(base_score=None, booster=None, colsample_bylevel=None,
              colsample_bynode=None, colsample_bytree=None, gamma=None,
              gpu_id=None, importance_type='gain', interaction_constraints=None,
              learning_rate=None, max_delta_step=None, max_depth=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              random_state=None, reg_alpha=None, reg_lambda=None,
              scale_pos_weight=None, subsample=None, tree_method=None,
              validate_parameters=None, verbosity=None):
Best Accuracy : 93.62%
Best Parameters :  {'eval_metric': 'error', 'learning_rate': 0.1}

----------------
```

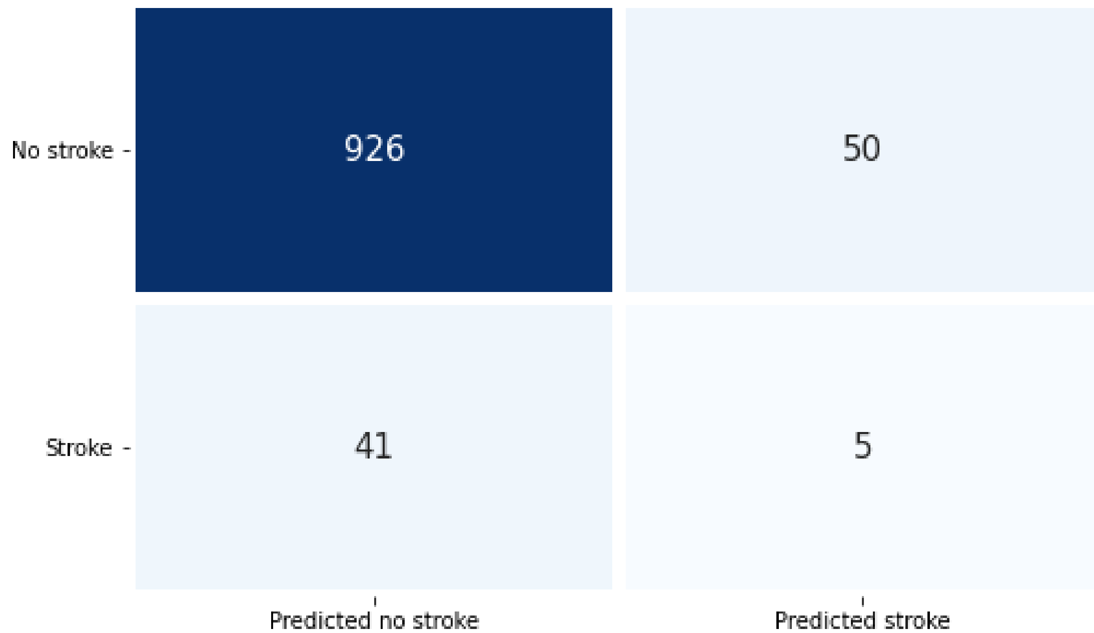
0.0.12 Model Evaluation

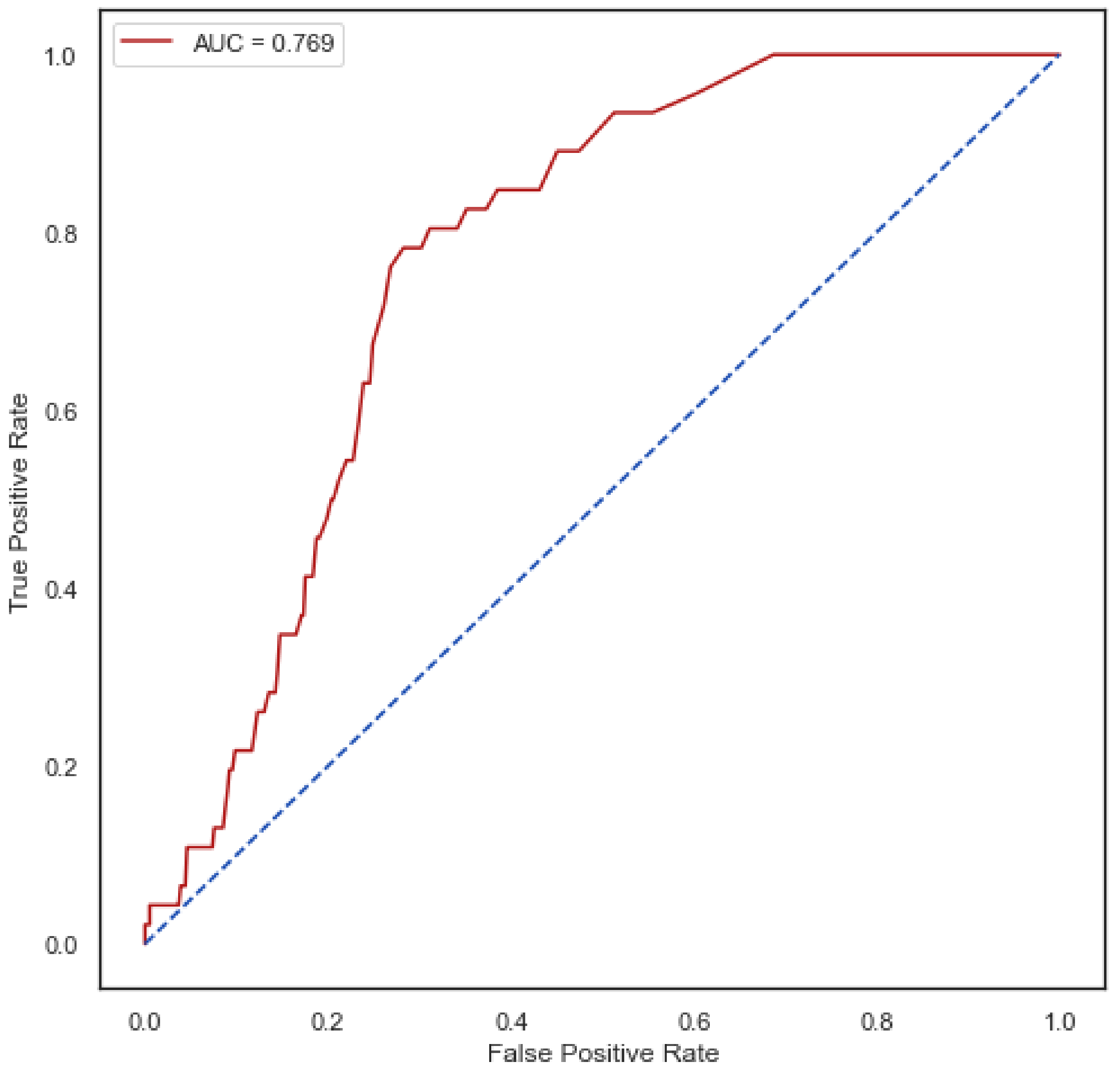
Now that we have the best hyperparameters we will work with the two best models, Random Forest and XGBoost.

[54]:
```
#Fitting RandomForest Model
classifier = RandomForestClassifier(criterion= 'entropy', n_estimators= 150,␣
 ↪random_state= 0)
classifier.fit(X_train_res, y_train_res)
```

```python
y_pred = classifier.predict(X_test)
y_prob = classifier.predict_proba(X_test)[:,1]
cm = confusion_matrix(y_test, y_pred)

print(classification_report(y_test, y_pred))
print(f'ROC AUC score: {roc_auc_score(y_test, y_prob)}')
print('Accuracy Score: ',accuracy_score(y_test, y_pred))

# Visualizing Confusion Matrix
plt.figure(figsize = (8, 5))
sns.heatmap(cm, cmap = 'Blues', annot = True, fmt = 'd', linewidths = 5, cbar =␣
↪False, annot_kws = {'fontsize': 15},
            yticklabels = ['No stroke', 'Stroke'], xticklabels = ['Predicted no␣
↪stroke', 'Predicted stroke'])
plt.yticks(rotation = 0)
plt.show()

# Roc AUC Curve
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_prob)
roc_auc = auc(false_positive_rate, true_positive_rate)

sns.set_theme(style = 'white')
plt.figure(figsize = (8, 8))
plt.plot(false_positive_rate,true_positive_rate, color = '#b01717', label =␣
↪'AUC = %0.3f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1], linestyle = '--', color = '#174ab0')
plt.axis('tight')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.legend()
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.96      0.95      0.95       976
           1       0.09      0.11      0.10        46

    accuracy                           0.91      1022
   macro avg       0.52      0.53      0.53      1022
weighted avg       0.92      0.91      0.91      1022

ROC AUC score: 0.769478349964362
Accuracy Score:  0.910958904109589
```

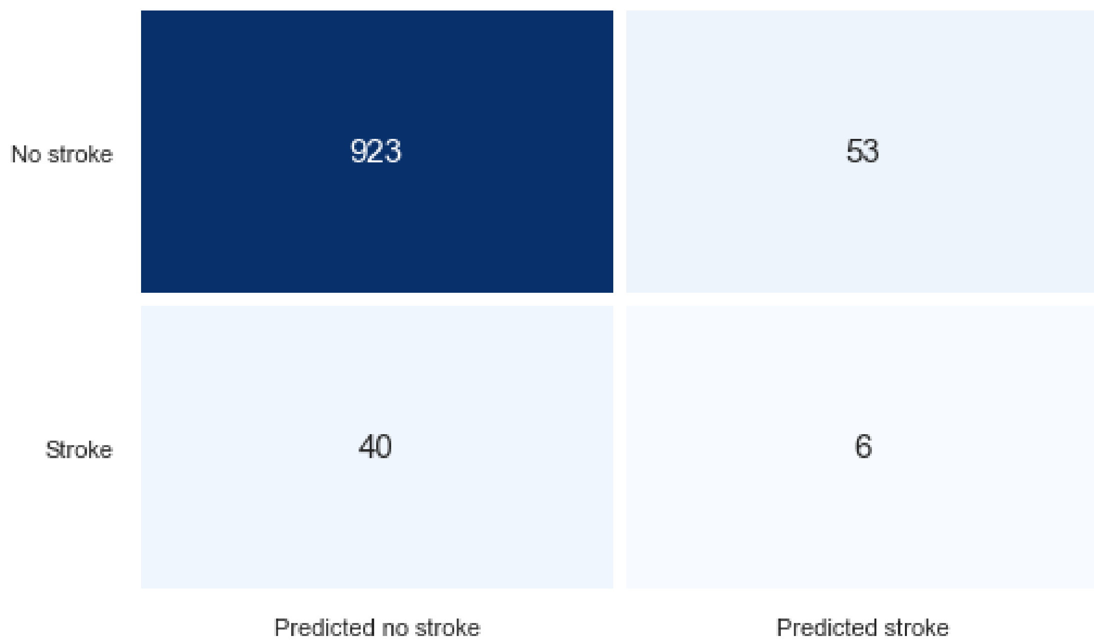

No stroke
Stroke
926
50
41
5
Predicted no stroke
Predicted stroke



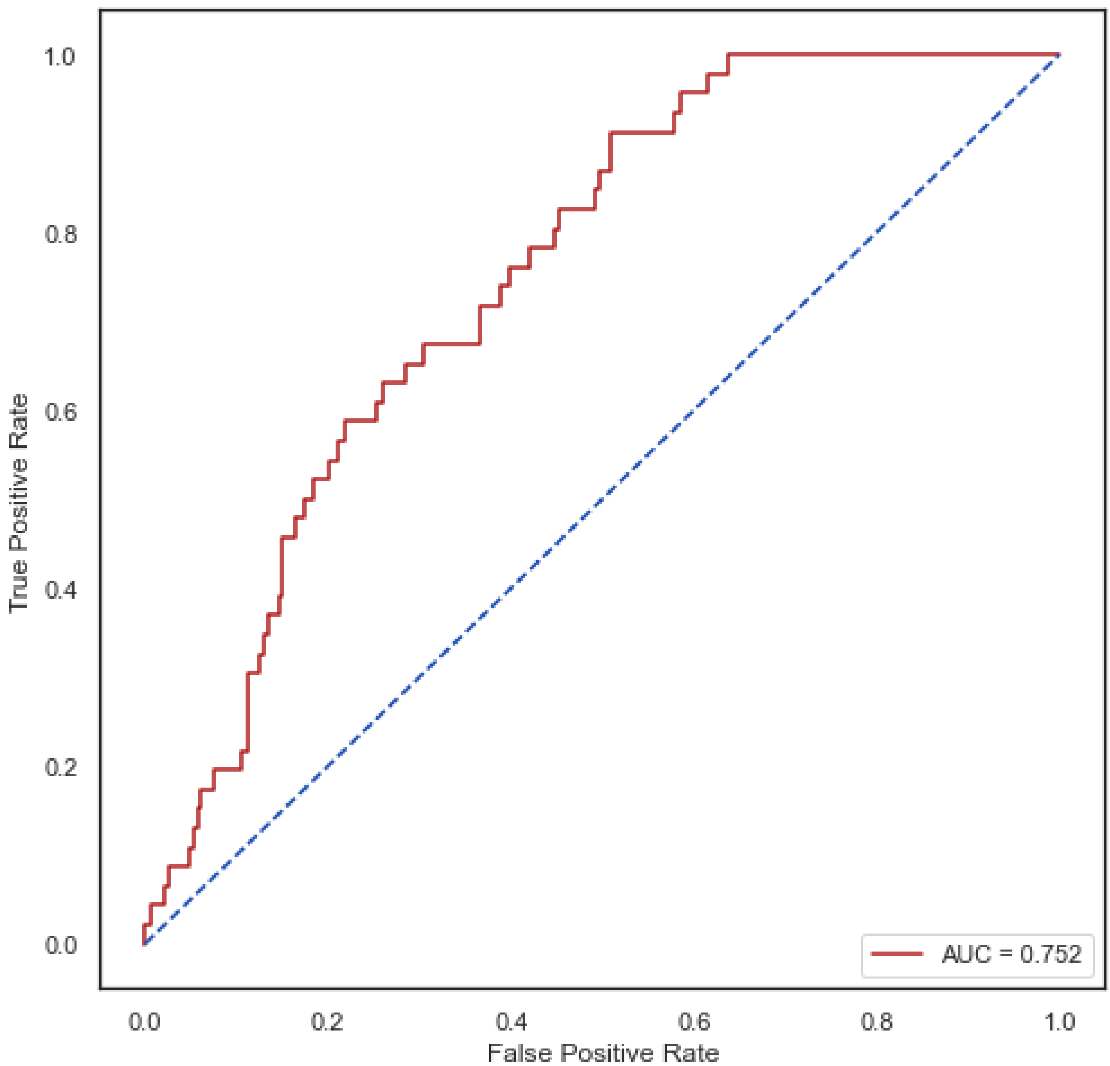
[55]:
```
#Fitting XGBClassifier Model
classifier = XGBClassifier(eval_metric= 'error', learning_rate= 0.1)
classifier.fit(X_train_res, y_train_res)
y_pred = classifier.predict(X_test)
y_prob = classifier.predict_proba(X_test)[:,1]
cm = confusion_matrix(y_test, y_pred)

print(classification_report(y_test, y_pred))
print(f'ROC AUC score: {roc_auc_score(y_test, y_prob)}')
print('Accuracy Score: ',accuracy_score(y_test, y_pred))

# Visualizing Confusion Matrix
plt.figure(figsize = (8, 5))
```

```python
sns.heatmap(cm, cmap = 'Blues', annot = True, fmt = 'd', linewidths = 5, cbar =␣
 ↪False, annot_kws = {'fontsize': 15},
            yticklabels = ['No stroke', 'Stroke'], xticklabels = ['Predicted no␣
 ↪stroke', 'Predicted stroke'])
plt.yticks(rotation = 0)
plt.show()

# Roc Curve
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_prob)
roc_auc = auc(false_positive_rate, true_positive_rate)

sns.set_theme(style = 'white')
plt.figure(figsize = (8, 8))
plt.plot(false_positive_rate,true_positive_rate, color = '#b01717', label =␣
 ↪'AUC = %0.3f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1], linestyle = '--', color = '#174ab0')
plt.axis('tight')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
```

```
              precision    recall  f1-score   support

           0       0.96      0.95      0.95       976
           1       0.10      0.13      0.11        46

    accuracy                           0.91      1022
   macro avg       0.53      0.54      0.53      1022
weighted avg       0.92      0.91      0.91      1022

ROC AUC score: 0.7519600855310049
Accuracy Score:  0.9090019569471625
```



[55]: `Text(0.5, 0, 'False Positive Rate')`



0.0.13 Conclusions

The models do a good job at predicting that someone will not have a stroke, but struggle with predicting if someone will have a stroke. Overall I'm happy with my results.