In [126…
```
print("Team 34_STROKE PREDICTION")
```

```
Team 34_STROKE PREDICTION
```

In [127…
```
print("187106_Aniketh Satharla **** 187136_Md. Saad Zemam **** 187164_Sunny Kanaujiya *
```

```
187106_Aniketh Satharla **** 187136_Md. Saad Zemam **** 187164_Sunny Kanaujiya **** 1871
65_T. Akash
```

In [128…
```
print("Importing the necessary libraries")
```

```
Importing the necessary libraries
```

In [129…
```
# To prevent the annoying warning from scikit learn package
import warnings
warnings.filterwarnings('ignore')
```

In [130…
```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns

sns.set_style('darkgrid')
cmap = sns.cm.mako_r

%matplotlib inline
```

In [131…
```
print("Importing the Data and calling head() and info() on the DataFrame")
```

```
Importing the Data and calling head() and info() on the DataFrame
```

In [132…
```
stroke = pd.read_csv(r"C:\Users\Pavilion\OneDrive\Documents\healthcare-dataset-stroke-d
```

In [133…
```
stroke.head()
```

Out[133…

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glu
0	9046	Male	67.0	0	1	Yes	Private	Urban	
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	
2	31112	Male	80.0	0	1	Yes	Private	Rural	
3	60182	Female	49.0	0	0	Yes	Private	Urban	
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural	

In [134…
```
stroke.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5110 entries, 0 to 5109
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5110 non-null   int64
```

```
 1   gender             5110 non-null   object 
 2   age                5110 non-null   float64
 3   hypertension       5110 non-null   int64  
 4   heart_disease      5110 non-null   int64  
 5   ever_married       5110 non-null   object 
 6   work_type          5110 non-null   object 
 7   Residence_type     5110 non-null   object 
 8   avg_glucose_level  5110 non-null   float64
 9   bmi                4909 non-null   float64
 10  smoking_status     5110 non-null   object 
 11  stroke             5110 non-null   int64  
dtypes: float64(3), int64(4), object(5)
memory usage: 479.2+ KB
```

In [135…

```
stroke.drop(columns=['id']).describe()
```

Out[135…

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

In [136…

```
print("Preprocessing Data before Exploratory Data Analysis")
```

```
Preprocessing Data before Exploratory Data Analysis
```

In [137…

```
# Round off Age
stroke['age'] = stroke['age'].apply(lambda x : round(x))

# BMI to NaN
stroke['bmi'] = stroke['bmi'].apply(lambda bmi_value: bmi_value if 12 < bmi_value < 60

# Sorting DataFrame based on Gender then on Age and using Forward Fill-ffill() to fill
stroke.sort_values(['gender', 'age'], inplace=True)
stroke.reset_index(drop=True, inplace=True)
stroke['bmi'].ffill(inplace=True)
```

In [138…

```
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   int64  
 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                5110 non-null   float64
 10  smoking_status     5110 non-null   object 
 11  stroke             5110 non-null   int64  
dtypes: float64(2), int64(5), object(5)
memory usage: 479.2+ KB
```

In [139…

```
print("Now we have Age Column as int64 and no missing values in Bmi Column")
```

```
Now we have Age Column as int64 and no missing values in Bmi Column
```

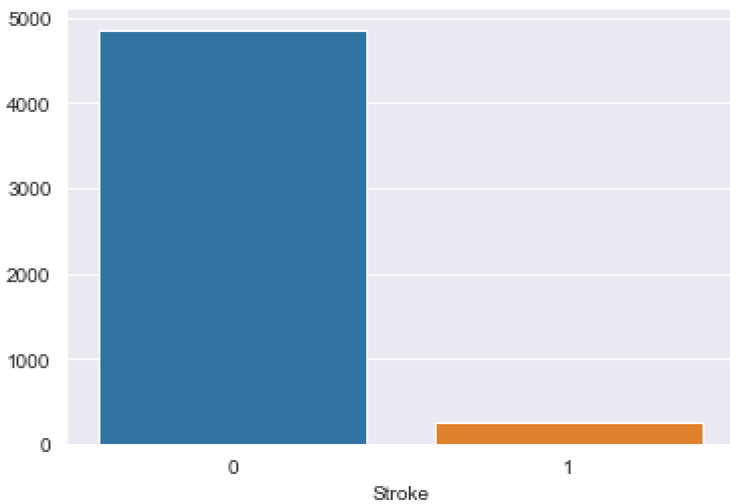
In [140…

```
print(" Exploratory Data Analysis on Stroke Prediction Data")
```

```
 Exploratory Data Analysis on Stroke Prediction Data
```

In [141…

```
# Checking if Data is balanced
xs = stroke['stroke'].value_counts().index
ys = stroke['stroke'].value_counts().values

ax = sns.barplot(xs, ys)
ax.set_xlabel("Stroke")
plt.show()
```



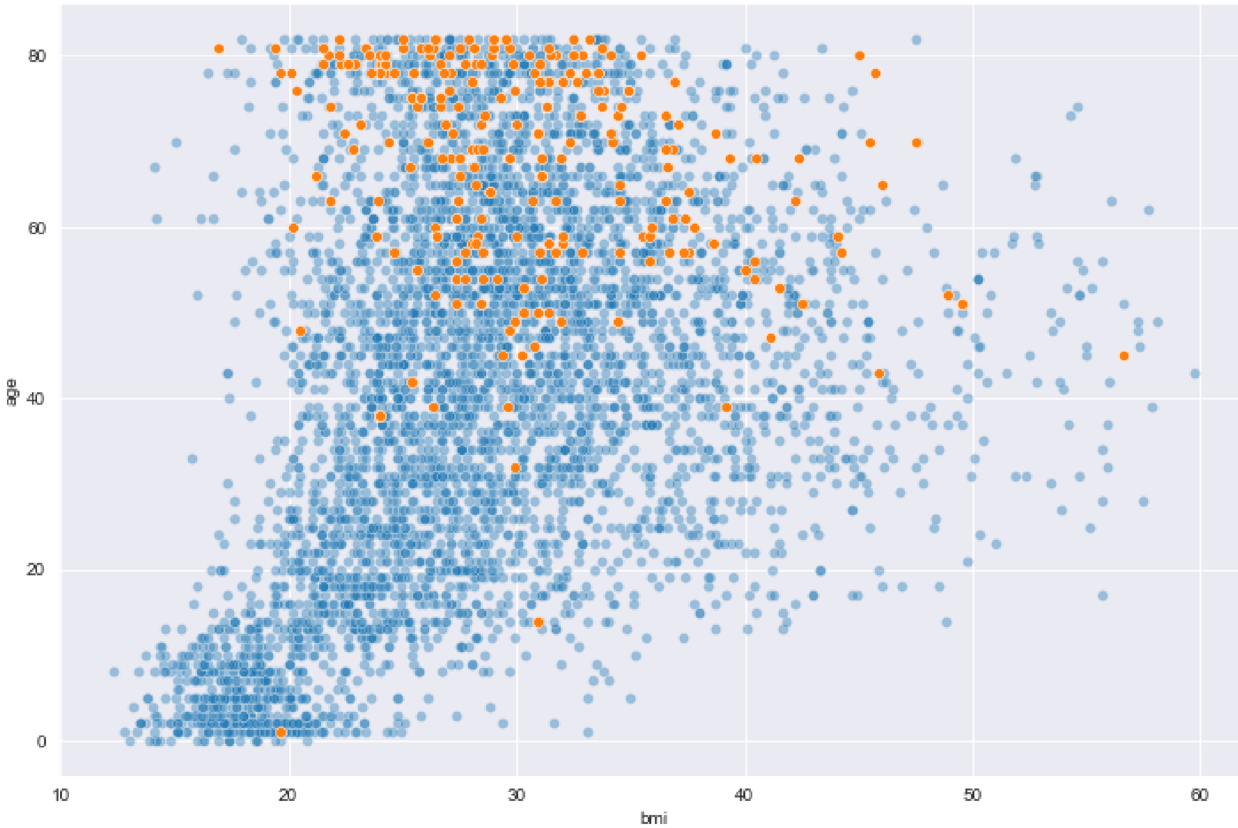
In [142…

```
print("As we can see from the above plot that the Data is not balanced which will resul
```

```
As we can see from the above plot that the Data is not balanced which will result in a b
ad model. To resolve this issue we can use SMOTE to balance the Data. This is will done
before fitting our data to the model.
```

In [143…

```
# Age vs BMI with hue = stroke
plt.figure(figsize=(12,8))
ax = sns.scatterplot(x="bmi", y="age", alpha=0.4, data=stroke[stroke['stroke'] == 0])
sns.scatterplot(x="bmi", y="age", alpha=1, data=stroke[stroke['stroke'] == 1], ax=ax)
plt.show()
```



In [144…

```
print("From the above Age vs BMI plot we can clearly see that when people attain an age
```

```
From the above Age vs BMI plot we can clearly see that when people attain an age of 40 o
r greater the chances of getting a stroke increases and after 60+ it tends to increase e
ven more. Also, people with a BMI of 25+ have shown a higher chances of encountering a s
troke. So, people with 40+ years and BMI of 25+ have a greater probability of encounteri
ng a stroke.
```

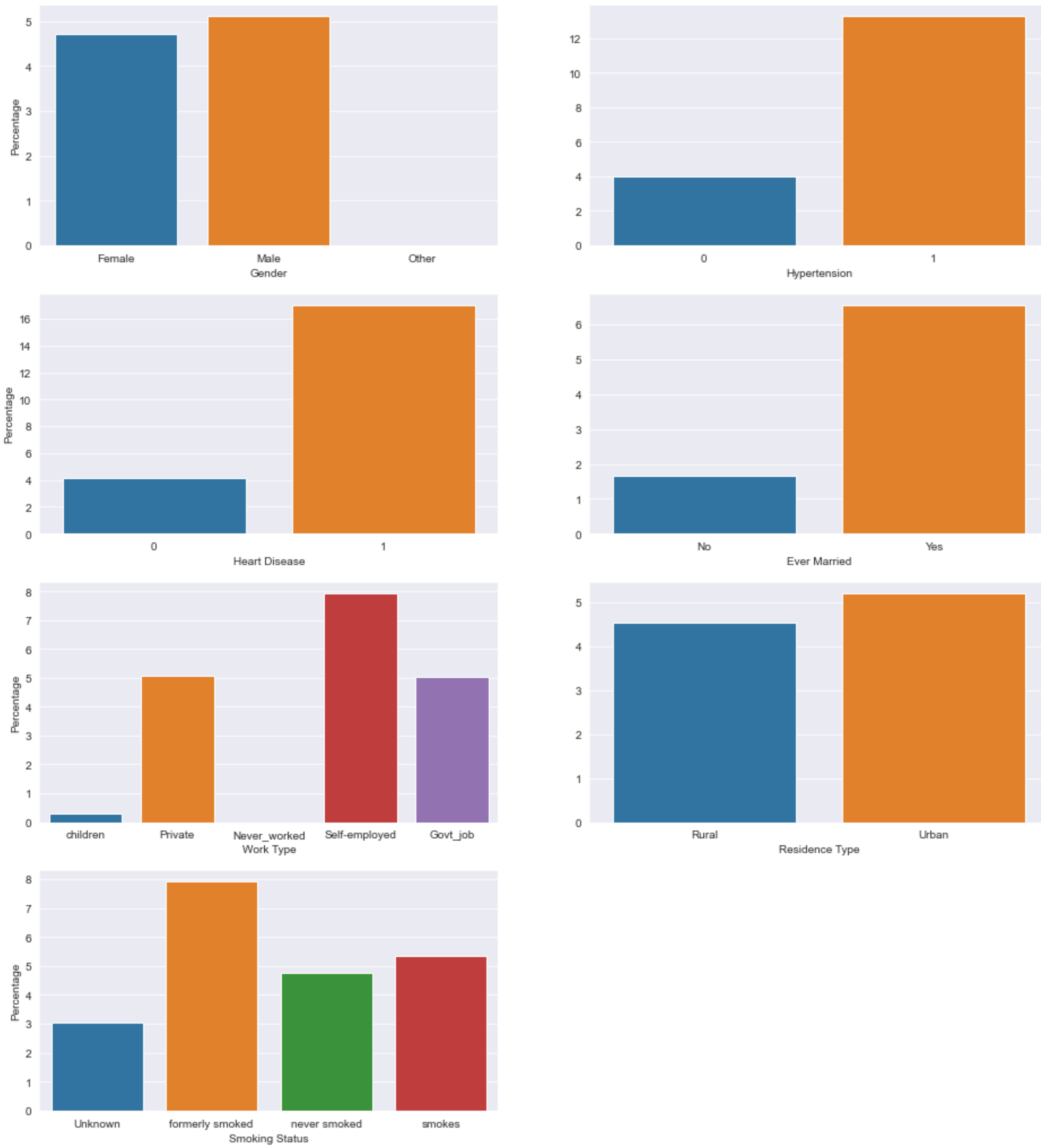
In [145…

```
# Age vs BMI with hue = stroke
plt.figure(figsize=(12,8))
ax = sns.scatterplot(x="bmi", y="avg_glucose_level", alpha=0.4, data=stroke[stroke['str
sns.scatterplot(x="bmi", y="avg_glucose_level", alpha=1, data=stroke[stroke['stroke'] =
plt.show()
```

In [146…

```
# Percentage of People
def plot_percent_of_stroke_in_each_category(df, column, axis):
    x_axis = []
    y_axis = []

    unique_values = df[column].unique()

    for value in unique_values:
        stroke_yes = len(df[(df[column] == value) & (df['stroke'] == 1)])
        total = len(df[df[column] == value])
        percentage = (stroke_yes/total) * 100
        x_axis.append(value)
        y_axis.append(percentage)

    sns.barplot(x_axis, y_axis, ax=axis)

columns = ['gender', 'hypertension', 'heart_disease', 'ever_married',
           'work_type', 'Residence_type', 'smoking_status']

fig, axes = plt.subplots(4, 2, figsize=(16, 18))
axes[3, 1].remove()

plot_percent_of_stroke_in_each_category(stroke, 'gender', axes[0,0])
axes[0,0].set_xlabel("Gender")
axes[0,0].set_ylabel("Percentage")

plot_percent_of_stroke_in_each_category(stroke, 'hypertension', axes[0,1])
axes[0,1].set_xlabel("Hypertension")

plot_percent_of_stroke_in_each_category(stroke, 'heart_disease', axes[1,0])
axes[1,0].set_xlabel("Heart Disease")
axes[1,0].set_ylabel("Percentage")
```

```
plot_percent_of_stroke_in_each_category(stroke, 'ever_married', axes[1,1])
axes[1,1].set_xlabel("Ever Married")


plot_percent_of_stroke_in_each_category(stroke, 'work_type', axes[2,0])
axes[2,0].set_xlabel("Work Type")
axes[2,0].set_ylabel("Percentage")

plot_percent_of_stroke_in_each_category(stroke, 'Residence_type', axes[2,1])
axes[2,1].set_xlabel("Residence Type")

plot_percent_of_stroke_in_each_category(stroke, 'smoking_status', axes[3,0])
axes[3,0].set_xlabel("Smoking Status")
axes[3,0].set_ylabel("Percentage")

plt.show()
```



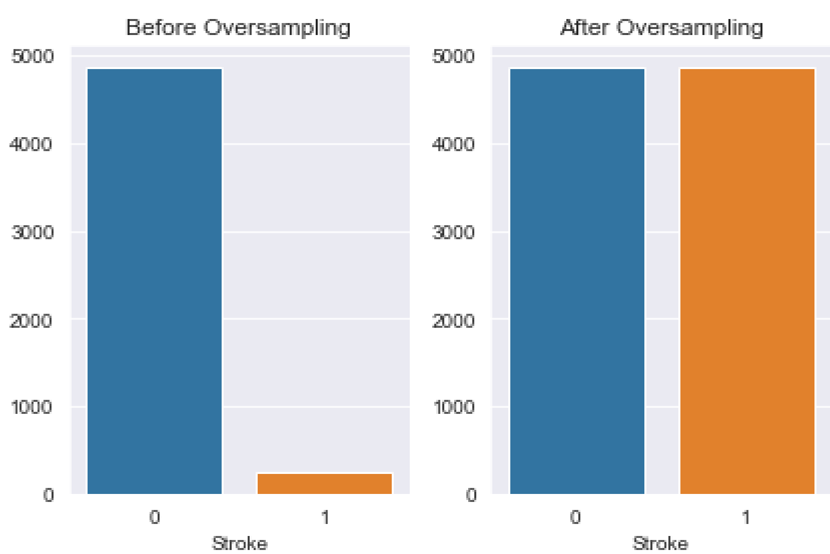
In [147…
```
print("Preparing the Data for Prediction")
```

```
Preparing the Data for Prediction
```

In [148…
```
#Converting Categorical Data to Numerical
gender_dict = {'Male': 0, 'Female': 1, 'Other': 2}
ever_married_dict = {'No': 0, 'Yes': 1}
work_type_dict = {'children': 0, 'Never_worked': 1, 'Govt_job': 2, 'Private': 3, 'Self-
residence_type_dict = {'Rural': 0, 'Urban': 1}
smoking_status_dict = {'Unknown': 0, 'never smoked': 1, 'formerly smoked':2, 'smokes':

stroke['gender'] = stroke['gender'].map(gender_dict)
stroke['ever_married'] = stroke['ever_married'].map(ever_married_dict)
stroke['work_type'] = stroke['work_type'].map(work_type_dict)
stroke['Residence_type'] = stroke['Residence_type'].map(residence_type_dict)
stroke['smoking_status'] = stroke['smoking_status'].map(smoking_status_dict)
```

In [149…
```
# Splitting into features and value to be predicted
X = stroke.drop(columns=['id', 'stroke'])
y = stroke['stroke']
```

In [150…
```
fig, (ax1, ax2) = plt.subplots(1, 2)

sns.barplot(x=['0', '1'], y =[sum(y == 0), sum(y == 1)], ax = ax1)
ax1.set_title("Before Oversampling")
ax1.set_xlabel('Stroke')

#Using SMOTE to balance the Data
from imblearn import under_sampling, over_sampling
from imblearn.over_sampling import SMOTE

sm = SMOTE(random_state = 2)
X, y = sm.fit_resample(X, y)

sns.barplot(x=['0', '1'], y =[sum(y == 0), sum(y == 1)], ax = ax2)
ax2.set_title("After Oversampling")
ax2.set_xlabel('Stroke')

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



In [151…
```
# Spliting the Data into Train and Test
```

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=4
```

In [152…

```
print("Creating a Model for Stroke Prediction")
```

```
Creating a Model for Stroke Prediction
```

In [153…

```
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, plot_confusion_matri

pipeline = make_pipeline(StandardScaler(), RandomForestClassifier())
pipeline.fit(X_train, y_train)
prediction = pipeline.predict(X_test)

print(f"Accuracy Score : {round(accuracy_score(y_test, prediction) * 100, 2)}%")
```

```
Accuracy Score : 93.9%
```

In [154…

```
print(classification_report(y_test, prediction))
```

```
              precision    recall  f1-score   support

           0       0.96      0.92      0.94      1422
           1       0.92      0.96      0.94      1495

    accuracy                           0.94      2917
   macro avg       0.94      0.94      0.94      2917
weighted avg       0.94      0.94      0.94      2917
```

In [155…

```
plot_confusion_matrix(pipeline, X_test, y_test, cmap=cmap)
plt.grid(False)
plt.show()
```