Brain Stroke Prediction using Machine Learning

In [ ]:

In [ ]:

Context

According to the World Health Organization (WHO) stroke is the 2nd leading cause of death globally, responsible for approximately 11% of total deaths. This dataset is used to predict whether a patient is likely to get stroke based on the input parameters like gender, age, various diseases, and smoking status. Each row in the data provides relavant information about the patient.

In [ ]:

Attribute Information

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

In [ ]:

Performing EDA-[Exploratory Data Analysis]

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import skew
from sklearn.linear_model import Ridge
from sklearn.metrics import r2_score

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

In [ ]:

In [2]:
```
df=pd.read_csv('Stroke_prediction.csv')
df
```

Out[2]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residen
0	9046	Male	67.0	0	1	Yes	Private	
1	51676	Female	61.0	0	0	Yes	Self-employed	
2	31112	Male	80.0	0	1	Yes	Private	
3	60182	Female	49.0	0	0	Yes	Private	
4	1665	Female	79.0	1	0	Yes	Self-employed	
...	...	...	...	...	...	...	...	
5105	18234	Female	80.0	1	0	Yes	Private	
5106	44873	Female	81.0	0	0	Yes	Self-employed	
5107	19723	Female	35.0	0	0	Yes	Self-employed	
5108	37544	Male	51.0	0	0	Yes	Private	
5109	44679	Female	44.0	0	0	Yes	Govt_job	

5110 rows × 12 columns

In [ ]:

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

Out[3]:

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

In [ ]:

In [4]:
```
df1=df.copy()
df1
```

Out[4]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residen
0	9046	Male	67.0	0	1	Yes	Private	
1	51676	Female	61.0	0	0	Yes	Self-employed	
2	31112	Male	80.0	0	1	Yes	Private	
3	60182	Female	49.0	0	0	Yes	Private	
4	1665	Female	79.0	1	0	Yes	Self-employed	
...	...	...	...	...	...	...	...	
5105	18234	Female	80.0	1	0	Yes	Private	
5106	44873	Female	81.0	0	0	Yes	Self-employed	
5107	19723	Female	35.0	0	0	Yes	Self-employed	
5108	37544	Male	51.0	0	0	Yes	Private	
5109	44679	Female	44.0	0	0	Yes	Govt_job	

5110 rows × 12 columns

In [ ]:

Initial Data Inspection

In [ ]:

In [5]:
```
df.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 [ ]:

In [6]:
```
print("Shape of dataset:", df.shape)
```

```
Shape of dataset: (5110, 12)
```

In [ ]:

In [7]:
```
print("Columns:", df.columns.tolist())
```

```
Columns: ['id', 'gender', 'age', 'hypertension', 'heart_disease', 'ever_married', 'w
ork_type', 'Residence_type', 'avg_glucose_level', 'bmi', 'smoking_status', 'stroke']
```

In [ ]:

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
id                     0
gender                 0
age                    0
hypertension           0
heart_disease          0
ever_married           0
work_type              0
Residence_type         0
avg_glucose_level      0
bmi                  201
smoking_status         0
stroke                 0
dtype: int64
```

In [ ]:

Handle Missing Values

In [9]:
```
missing_percent = df.isnull().mean() * 100
print(missing_percent)
```

```
id                   0.000000
gender               0.000000
age                  0.000000
hypertension         0.000000
heart_disease        0.000000
ever_married         0.000000
work_type            0.000000
Residence_type       0.000000
avg_glucose_level    0.000000
bmi                  3.933464
smoking_status       0.000000
stroke               0.000000
dtype: float64
```

In [ ]:

In [10]:
```
df['bmi'].unique()


#here the bmi indicates the body mass index where it is the ratio of height and wei
```

Out[10]:
```
array([36.6,  nan, 32.5, 34.4, 24. , 29. , 27.4, 22.8, 24.2, 29.7, 36.8,
       27.3, 28.2, 30.9, 37.5, 25.8, 37.8, 22.4, 48.9, 26.6, 27.2, 23.5,
       28.3, 44.2, 25.4, 22.2, 30.5, 26.5, 33.7, 23.1, 32. , 29.9, 23.9,
       28.5, 26.4, 20.2, 33.6, 38.6, 39.2, 27.7, 31.4, 36.5, 33.2, 32.8,
       40.4, 25.3, 30.2, 47.5, 20.3, 30. , 28.9, 28.1, 31.1, 21.7, 27. ,
       24.1, 45.9, 44.1, 22.9, 29.1, 32.3, 41.1, 25.6, 29.8, 26.3, 26.2,
       29.4, 24.4, 28. , 28.8, 34.6, 19.4, 30.3, 41.5, 22.6, 56.6, 27.1,
       31.3, 31. , 31.7, 35.8, 28.4, 20.1, 26.7, 38.7, 34.9, 25. , 23.8,
       21.8, 27.5, 24.6, 32.9, 26.1, 31.9, 34.1, 36.9, 37.3, 45.7, 34.2,
       23.6, 22.3, 37.1, 45. , 25.5, 30.8, 37.4, 34.5, 27.9, 29.5, 46. ,
       42.5, 35.5, 26.9, 45.5, 31.5, 33. , 23.4, 30.7, 20.5, 21.5, 40. ,
       28.6, 42.2, 29.6, 35.4, 16.9, 26.8, 39.3, 32.6, 35.9, 21.2, 42.4,
       40.5, 36.7, 29.3, 19.6, 18. , 17.6, 19.1, 50.1, 17.7, 54.6, 35. ,
       22. , 39.4, 19.7, 22.5, 25.2, 41.8, 60.9, 23.7, 24.5, 31.2, 16. ,
       31.6, 25.1, 24.8, 18.3, 20. , 19.5, 36. , 35.3, 40.1, 43.1, 21.4,
       34.3, 27.6, 16.5, 24.3, 25.7, 21.9, 38.4, 25.9, 54.7, 18.6, 24.9,
       48.2, 20.7, 39.5, 23.3, 64.8, 35.1, 43.6, 21. , 47.3, 16.6, 21.6,
       15.5, 35.6, 16.7, 41.9, 16.4, 17.1, 29.2, 37.9, 44.6, 39.6, 40.3,
       41.6, 39. , 23.2, 18.9, 36.1, 36.3, 46.5, 16.8, 46.6, 35.2, 20.9,
       13.8, 31.8, 15.3, 38.2, 45.2, 17. , 49.8, 27.8, 60.2, 23. , 22.1,
       26. , 44.3, 51. , 39.7, 34.7, 21.3, 41.2, 34.8, 19.2, 35.7, 40.8,
       24.7, 19. , 32.4, 34. , 28.7, 32.1, 51.5, 20.4, 30.6, 71.9, 19.3,
       40.9, 17.2, 16.1, 16.2, 40.6, 18.4, 21.1, 42.3, 32.2, 50.2, 17.5,
       18.7, 42.1, 47.8, 20.8, 30.1, 17.3, 36.4, 12. , 36.2, 55.7, 14.4,
       43. , 41.7, 33.8, 43.9, 22.7, 57.5, 37. , 38.5, 16.3, 44. , 32.7,
       54.2, 40.2, 33.3, 17.4, 41.3, 52.3, 14.6, 17.8, 46.1, 33.1, 18.1,
       43.8, 50.3, 38.9, 43.7, 39.9, 15.9, 19.8, 12.3, 78. , 38.3, 41. ,
       42.6, 43.4, 15.1, 20.6, 33.5, 43.2, 30.4, 38. , 33.4, 44.9, 44.7,
       37.6, 39.8, 53.4, 55.2, 42. , 37.2, 42.8, 18.8, 42.9, 14.3, 37.7,
       48.4, 50.6, 46.2, 49.5, 43.3, 33.9, 18.5, 44.5, 45.4, 55. , 54.8,
       19.9, 17.9, 15.6, 52.8, 15.2, 66.8, 55.1, 18.2, 48.5, 55.9, 57.3,
       10.3, 14.1, 15.7, 56. , 44.8, 13.4, 51.8, 38.1, 57.7, 44.4, 38.8,
       49.3, 39.1, 54. , 56.1, 97.6, 53.9, 13.7, 11.5, 41.4, 14.2, 49.4,
       15.4, 45.1, 49.2, 48.7, 53.8, 42.7, 48.8, 52.7, 53.5, 50.5, 15.8,
       45.3, 14.8, 51.9, 63.3, 40.7, 61.2, 48. , 46.8, 48.3, 58.1, 50.4,
       11.3, 12.8, 13.5, 14.5, 15. , 59.7, 47.4, 52.5, 13.2, 52.9, 61.6,
       49.9, 54.3, 47.9, 13. , 13.9, 50.9, 57.2, 64.4, 92. , 50.8, 57.9,
       45.8, 47.6, 14. , 46.4, 46.9, 47.1, 13.3, 48.1, 51.7, 46.3, 54.1,
       14.9])
```

In [11]:
```
#Drop ID column
```

In [12]:
```
df.drop(columns=["id"], inplace=True)
```

REPLACING THE NAN VALUES WITH ITS MEDIAN IN bmi

In [13]:
```
df['bmi'].fillna(df['bmi'].median(), inplace=True)
```

In [14]:
```
df['bmi'].unique() #- Rplace sucessfull
```

Out[14]:
```
array([36.6, 28.1, 32.5, 34.4, 24. , 29. , 27.4, 22.8, 24.2, 29.7, 36.8,
       27.3, 28.2, 30.9, 37.5, 25.8, 37.8, 22.4, 48.9, 26.6, 27.2, 23.5,
       28.3, 44.2, 25.4, 22.2, 30.5, 26.5, 33.7, 23.1, 32. , 29.9, 23.9,
       28.5, 26.4, 20.2, 33.6, 38.6, 39.2, 27.7, 31.4, 36.5, 33.2, 32.8,
       40.4, 25.3, 30.2, 47.5, 20.3, 30. , 28.9, 31.1, 21.7, 27. , 24.1,
       45.9, 44.1, 22.9, 29.1, 32.3, 41.1, 25.6, 29.8, 26.3, 26.2, 29.4,
       24.4, 28. , 28.8, 34.6, 19.4, 30.3, 41.5, 22.6, 56.6, 27.1, 31.3,
       31. , 31.7, 35.8, 28.4, 20.1, 26.7, 38.7, 34.9, 25. , 23.8, 21.8,
       27.5, 24.6, 32.9, 26.1, 31.9, 34.1, 36.9, 37.3, 45.7, 34.2, 23.6,
       22.3, 37.1, 45. , 25.5, 30.8, 37.4, 34.5, 27.9, 29.5, 46. , 42.5,
       35.5, 26.9, 45.5, 31.5, 33. , 23.4, 30.7, 20.5, 21.5, 40. , 28.6,
       42.2, 29.6, 35.4, 16.9, 26.8, 39.3, 32.6, 35.9, 21.2, 42.4, 40.5,
       36.7, 29.3, 19.6, 18. , 17.6, 19.1, 50.1, 17.7, 54.6, 35. , 22. ,
       39.4, 19.7, 22.5, 25.2, 41.8, 60.9, 23.7, 24.5, 31.2, 16. , 31.6,
       25.1, 24.8, 18.3, 20. , 19.5, 36. , 35.3, 40.1, 43.1, 21.4, 34.3,
       27.6, 16.5, 24.3, 25.7, 21.9, 38.4, 25.9, 54.7, 18.6, 24.9, 48.2,
       20.7, 39.5, 23.3, 64.8, 35.1, 43.6, 21. , 47.3, 16.6, 21.6, 15.5,
       35.6, 16.7, 41.9, 16.4, 17.1, 29.2, 37.9, 44.6, 39.6, 40.3, 41.6,
       39. , 23.2, 18.9, 36.1, 36.3, 46.5, 16.8, 46.6, 35.2, 20.9, 13.8,
       31.8, 15.3, 38.2, 45.2, 17. , 49.8, 27.8, 60.2, 23. , 22.1, 26. ,
       44.3, 51. , 39.7, 34.7, 21.3, 41.2, 34.8, 19.2, 35.7, 40.8, 24.7,
       19. , 32.4, 34. , 28.7, 32.1, 51.5, 20.4, 30.6, 71.9, 19.3, 40.9,
       17.2, 16.1, 16.2, 40.6, 18.4, 21.1, 42.3, 32.2, 50.2, 17.5, 18.7,
       42.1, 47.8, 20.8, 30.1, 17.3, 36.4, 12. , 36.2, 55.7, 14.4, 43. ,
       41.7, 33.8, 43.9, 22.7, 57.5, 37. , 38.5, 16.3, 44. , 32.7, 54.2,
       40.2, 33.3, 17.4, 41.3, 52.3, 14.6, 17.8, 46.1, 33.1, 18.1, 43.8,
       50.3, 38.9, 43.7, 39.9, 15.9, 19.8, 12.3, 78. , 38.3, 41. , 42.6,
       43.4, 15.1, 20.6, 33.5, 43.2, 30.4, 38. , 33.4, 44.9, 44.7, 37.6,
       39.8, 53.4, 55.2, 42. , 37.2, 42.8, 18.8, 42.9, 14.3, 37.7, 48.4,
       50.6, 46.2, 49.5, 43.3, 33.9, 18.5, 44.5, 45.4, 55. , 54.8, 19.9,
       17.9, 15.6, 52.8, 15.2, 66.8, 55.1, 18.2, 48.5, 55.9, 57.3, 10.3,
       14.1, 15.7, 56. , 44.8, 13.4, 51.8, 38.1, 57.7, 44.4, 38.8, 49.3,
       39.1, 54. , 56.1, 97.6, 53.9, 13.7, 11.5, 41.4, 14.2, 49.4, 15.4,
       45.1, 49.2, 48.7, 53.8, 42.7, 48.8, 52.7, 53.5, 50.5, 15.8, 45.3,
       14.8, 51.9, 63.3, 40.7, 61.2, 48. , 46.8, 48.3, 58.1, 50.4, 11.3,
       12.8, 13.5, 14.5, 15. , 59.7, 47.4, 52.5, 13.2, 52.9, 61.6, 49.9,
       54.3, 47.9, 13. , 13.9, 50.9, 57.2, 64.4, 92. , 50.8, 57.9, 45.8,
       47.6, 14. , 46.4, 46.9, 47.1, 13.3, 48.1, 51.7, 46.3, 54.1, 14.9])
```

In [ ]:

Data Types and Conversion

In [15]:
```
cat_cols = ['gender', 'ever_married', 'work_type', 'Residence_type', 'smoking_statu
for col in cat_cols:
    df[col] = df[col].astype('category')
```

In [16]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5110 entries, 0 to 5109
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   gender             5110 non-null   category
 1   age                5110 non-null   float64
 2   hypertension       5110 non-null   int64
 3   heart_disease      5110 non-null   int64
 4   ever_married       5110 non-null   category
 5   work_type          5110 non-null   category
 6   Residence_type     5110 non-null   category
 7   avg_glucose_level  5110 non-null   float64
 8   bmi                5110 non-null   float64
 9   smoking_status     5110 non-null   category
 10  stroke             5110 non-null   int64
dtypes: category(5), float64(3), int64(3)
memory usage: 265.4 KB
```

In [ ]:

Statistical Summary

In [17]:
```
df.describe()
```

Out[17]:

	age	hypertension	heart_disease	avg_glucose_level	bmi	strok
count	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	5110.00000
mean	43.226614	0.097456	0.054012	106.147677	28.862035	0.04872
std	22.612647	0.296607	0.226063	45.283560	7.699562	0.21532
min	0.080000	0.000000	0.000000	55.120000	10.300000	0.00000
25%	25.000000	0.000000	0.000000	77.245000	23.800000	0.00000
50%	45.000000	0.000000	0.000000	91.885000	28.100000	0.00000
75%	61.000000	0.000000	0.000000	114.090000	32.800000	0.00000
max	82.000000	1.000000	1.000000	271.740000	97.600000	1.00000

Row Meaning ---------- count Total number of non-missing (non-NaN) values in that column mean The average value std Standard deviation (how spread out the values are) min Minimum value in the column 25% 25th percentile (lower quartile) 50% Median (middle value; 50th percentile) 75% 75th percentile (upper quartile) max Maximum value in the column

In [ ]:

In [18]:
```
for col in cat_cols:
    print(f"\nValue counts for {col}:\n", df[col].value_counts())
```

```
Value counts for gender:
 gender
Female    2994
Male      2115
Other        1
Name: count, dtype: int64

Value counts for ever_married:
 ever_married
Yes    3353
No     1757
Name: count, dtype: int64

Value counts for work_type:
 work_type
Private          2925
Self-employed     819
children          687
Govt_job          657
Never_worked       22
Name: count, dtype: int64

Value counts for Residence_type:
 Residence_type
Urban    2596
Rural    2514
Name: count, dtype: int64

Value counts for smoking_status:
 smoking_status
never smoked       1892
Unknown            1544
formerly smoked     885
smokes              789
Name: count, dtype: int64
```

In [ ]:

In [19]:
```
num_df = df.select_dtypes(include=['int64', 'float64'])

num_df
```

Out[19]:

	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	28.1	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	28.1	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

5110 rows × 6 columns

In [ ]:

In [20]:

```
for i in num_df:
    print(f"\nValue counts for {i}:\n", df[i].value_counts())
```

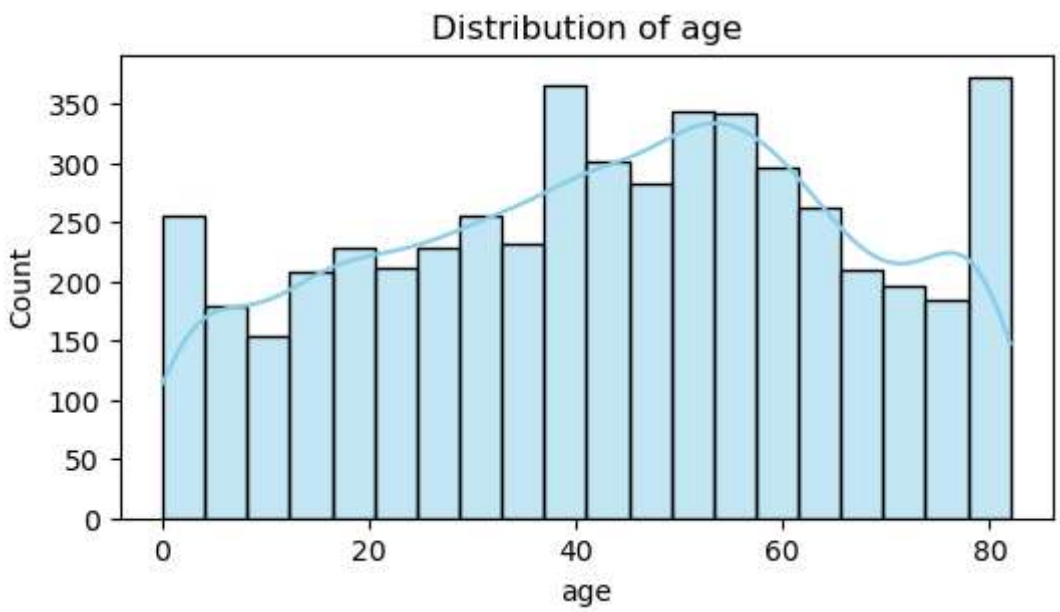
```
Value counts for age:
 age
78.00    102
57.00     95
52.00     90
54.00     87
51.00     86
        ...
1.40       3
0.48       3
0.16       3
0.08       2
0.40       2
Name: count, Length: 104, dtype: int64

Value counts for hypertension:
 hypertension
0    4612
1     498
Name: count, dtype: int64

Value counts for heart_disease:
 heart_disease
0    4834
1     276
Name: count, dtype: int64

Value counts for avg_glucose_level:
 avg_glucose_level
93.88     6
73.00     5
72.49     5
91.85     5
91.68     5
         ..
61.98     1
91.01     1
120.03    1
138.51    1
118.41    1
Name: count, Length: 3979, dtype: int64

Value counts for bmi:
 bmi
28.1    230
28.7     41
28.4     38
27.7     37
26.1     37
       ...
47.9      1
13.0      1
13.9      1
54.1      1
14.9      1
Name: count, Length: 418, dtype: int64
```

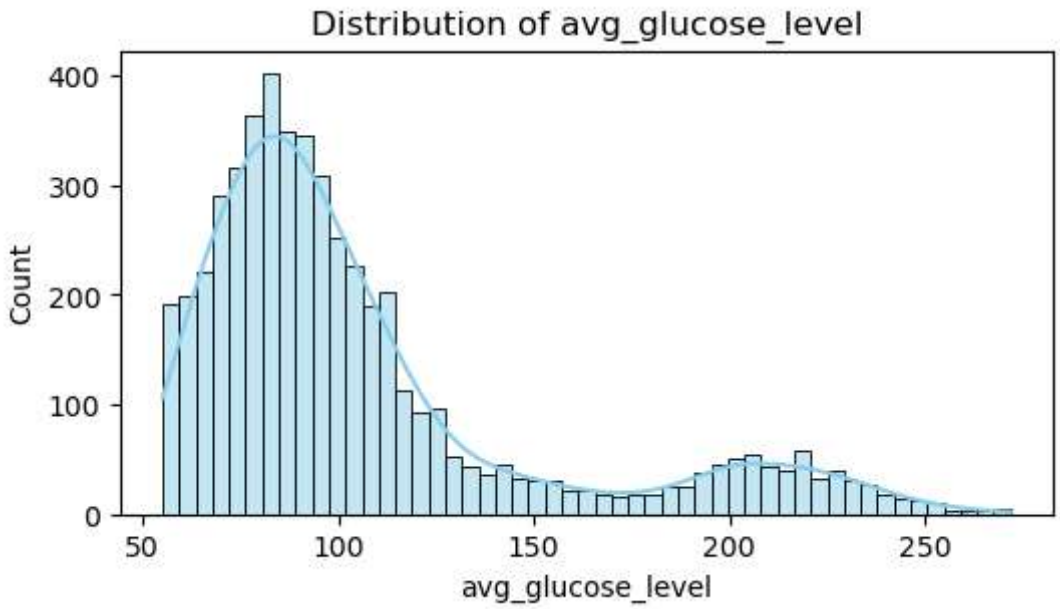
```
Value counts for stroke:
 stroke
0    4861
1     249
Name: count, dtype: int64
```

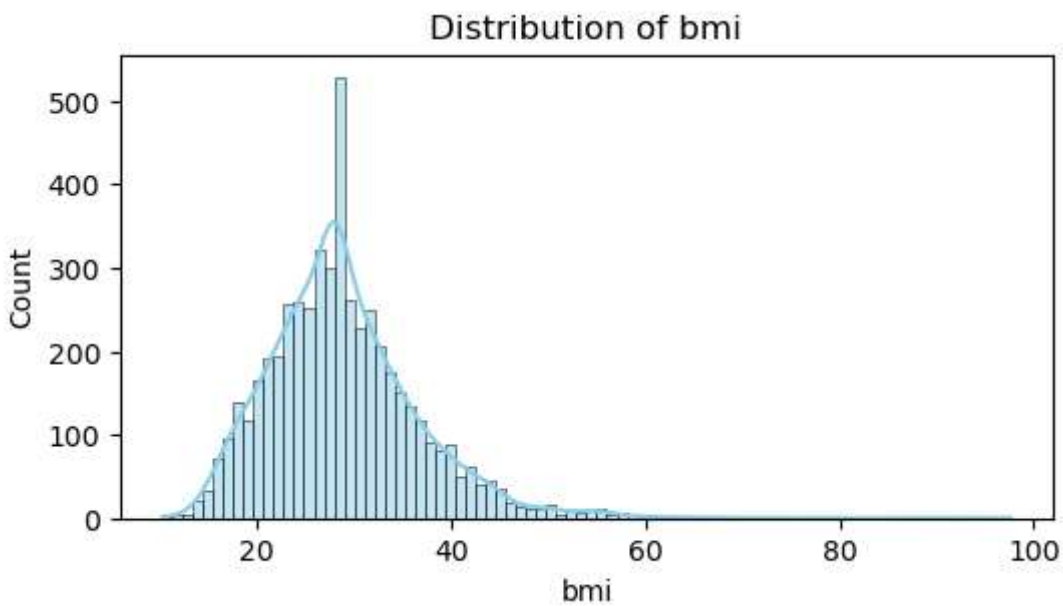
In [ ]:

Univariate Analysis

In [21]:
```
numerical_cols = ['age', 'avg_glucose_level', 'bmi']

for col in numerical_cols:
    plt.figure(figsize=(6,3))
    sns.histplot(df[col], kde=True, color='skyblue')
    plt.title(f'Distribution of {col}')
    plt.show()
```





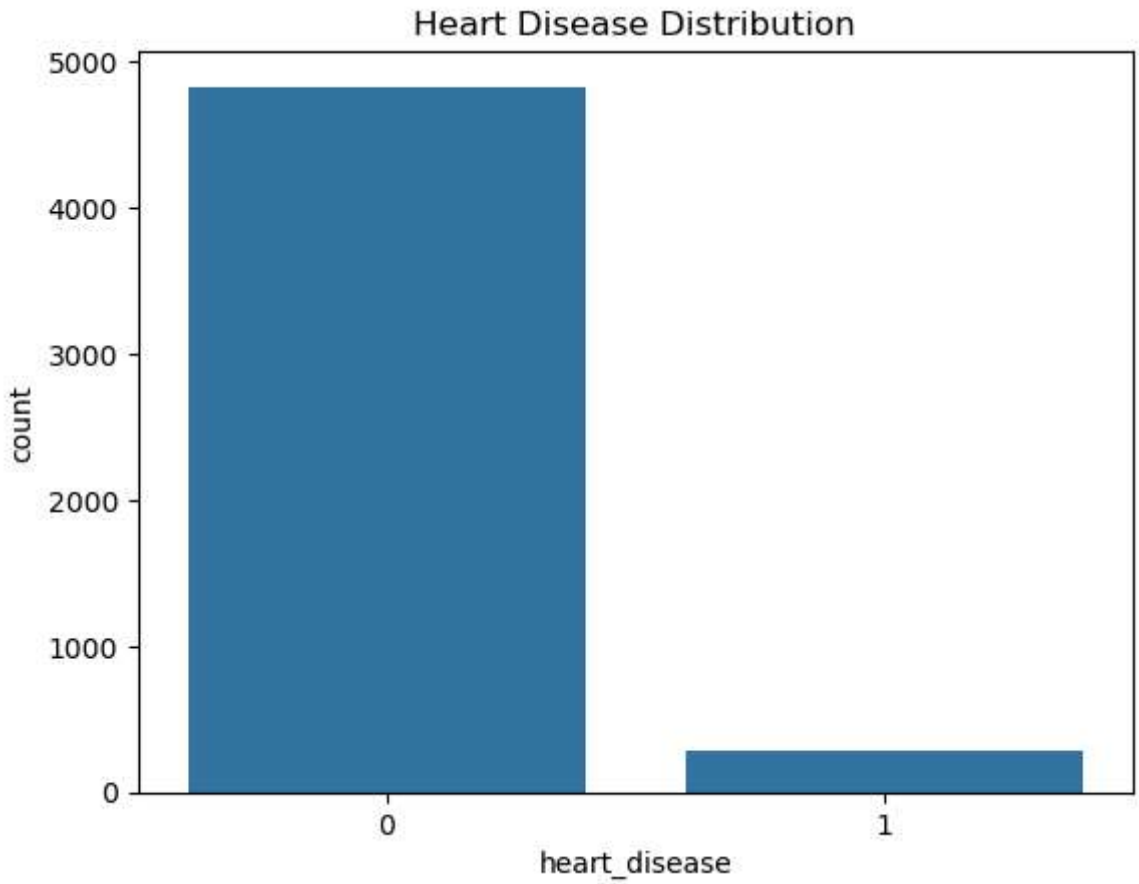


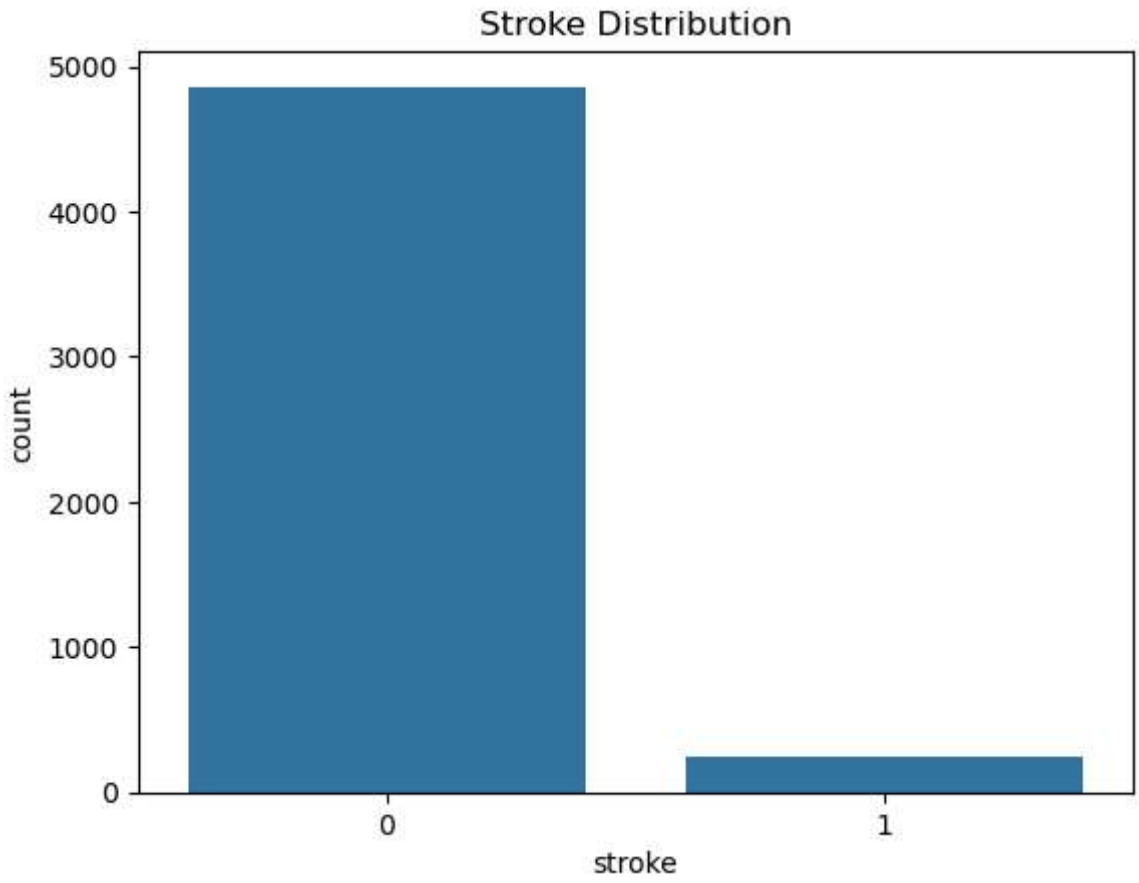
In [ ]:

Distribution of Target Variables

In [ ]:

In [22]:
```
# Heart Disease
sns.countplot(x='heart_disease', data=df)
plt.title("Heart Disease Distribution")
plt.show()

# Stroke
sns.countplot(x='stroke', data=df)
plt.title("Stroke Distribution")
plt.show()
```


Heart Disease Distribution
5000
4000
3000
2000
1000
0
count
0
1
heart_disease


Stroke Distribution
5000
4000
3000
2000
1000
0
count
0
1
stroke

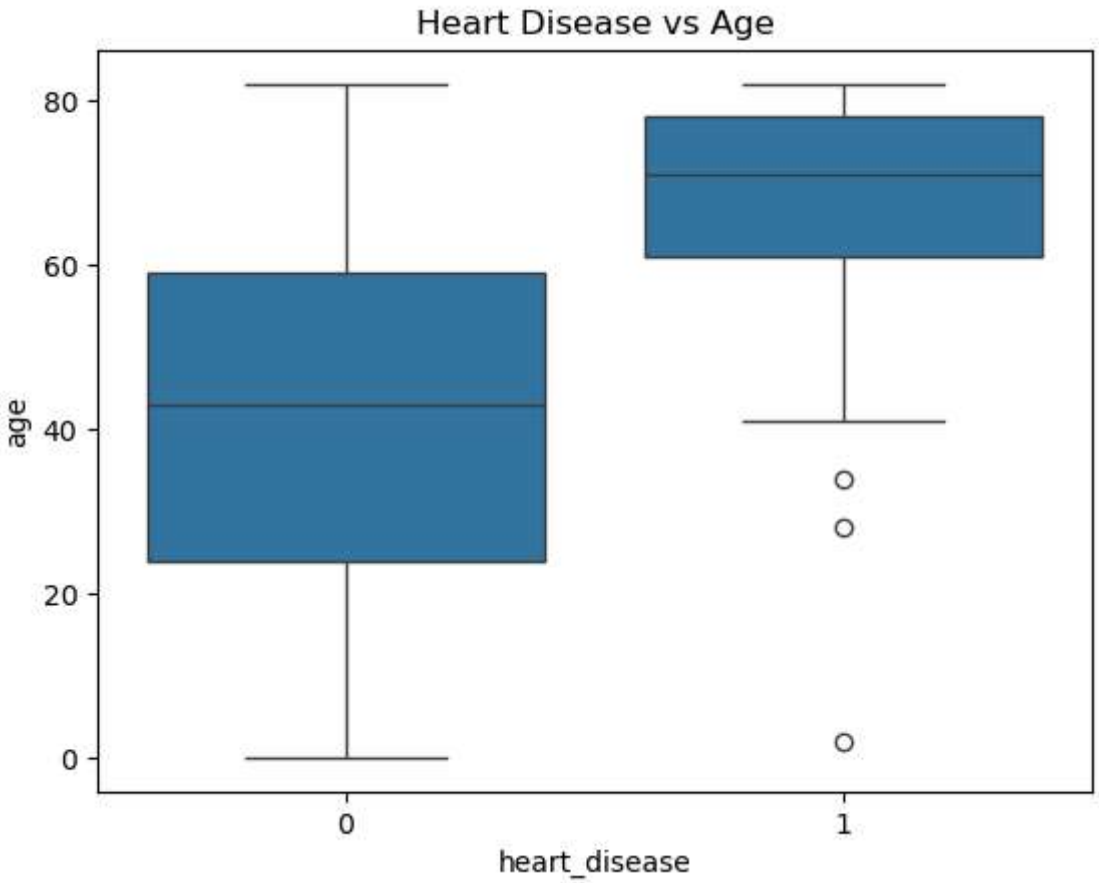
In [ ]:

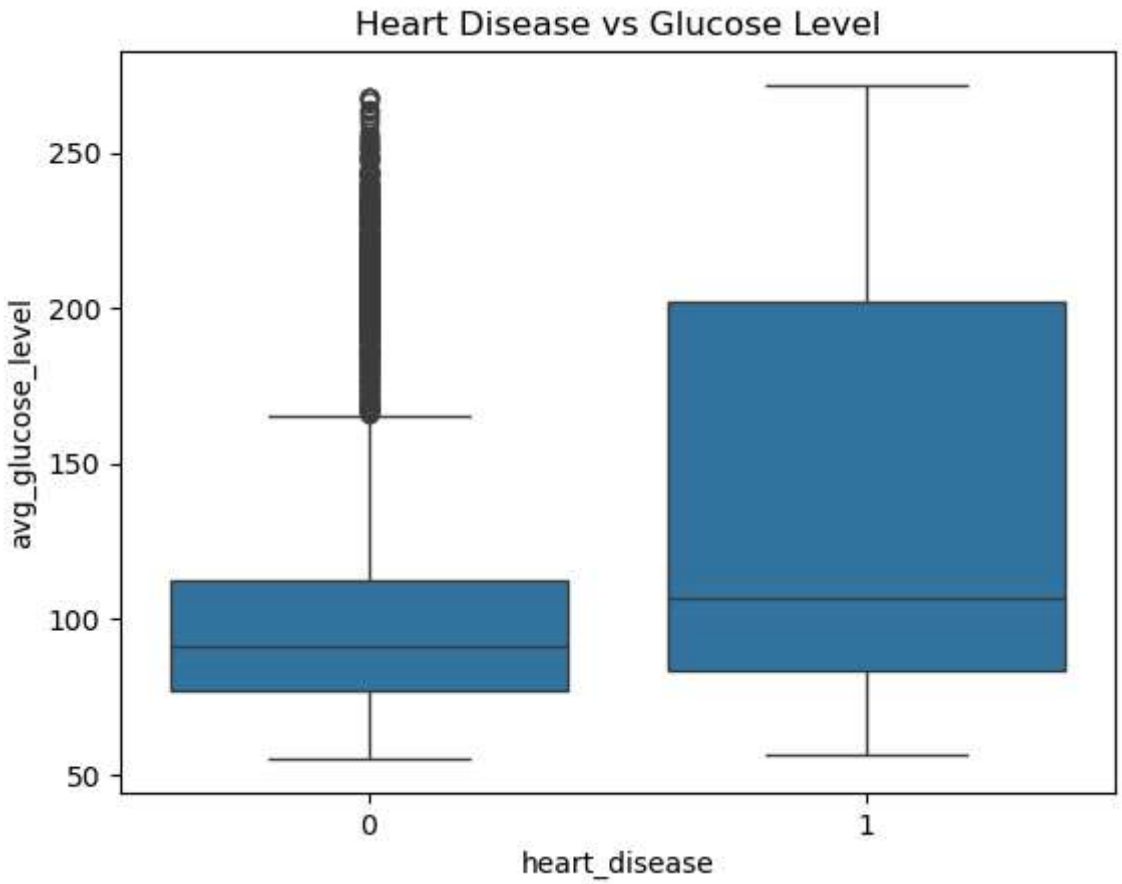
Bivariate Analysis

In [ ]:

In [ ]:

In [23]:
```
sns.boxplot(x='heart_disease', y='age', data=df)
plt.title("Heart Disease vs Age")
plt.show()

sns.boxplot(x='heart_disease', y='avg_glucose_level', data=df)
plt.title("Heart Disease vs Glucose Level")
plt.show()
```

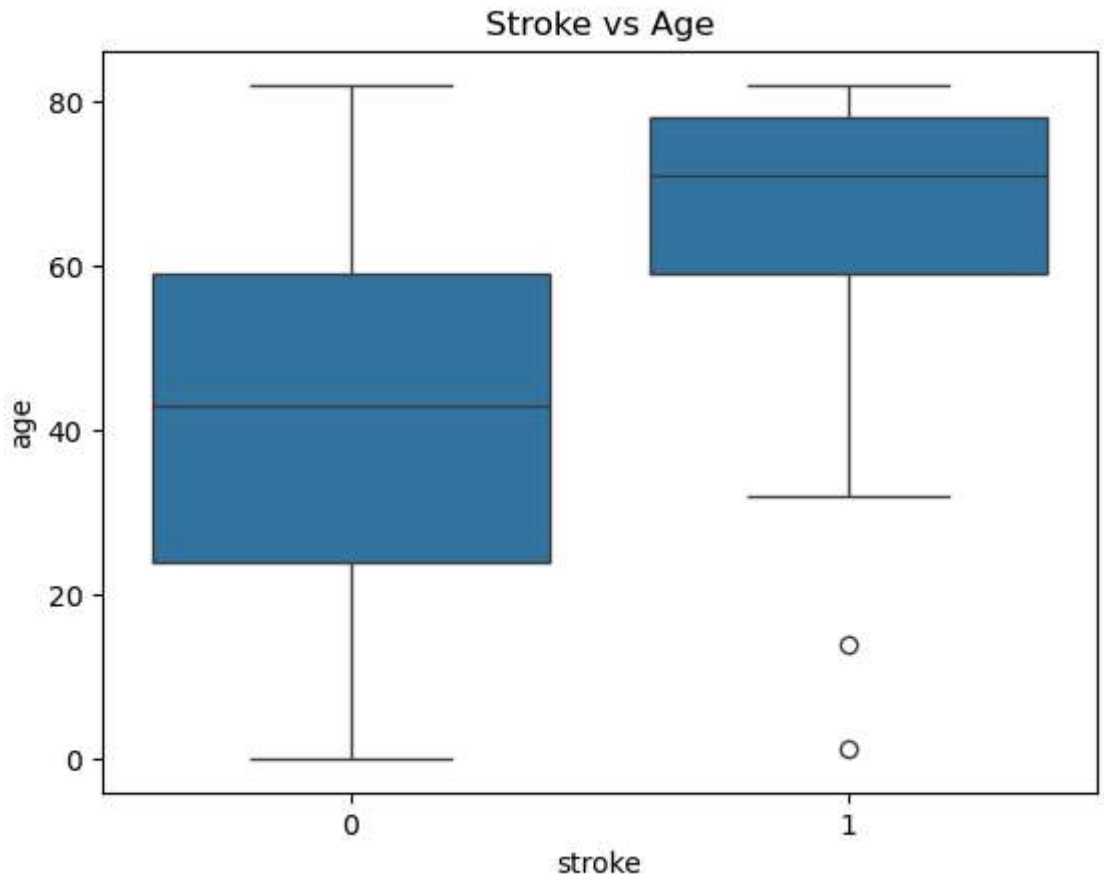


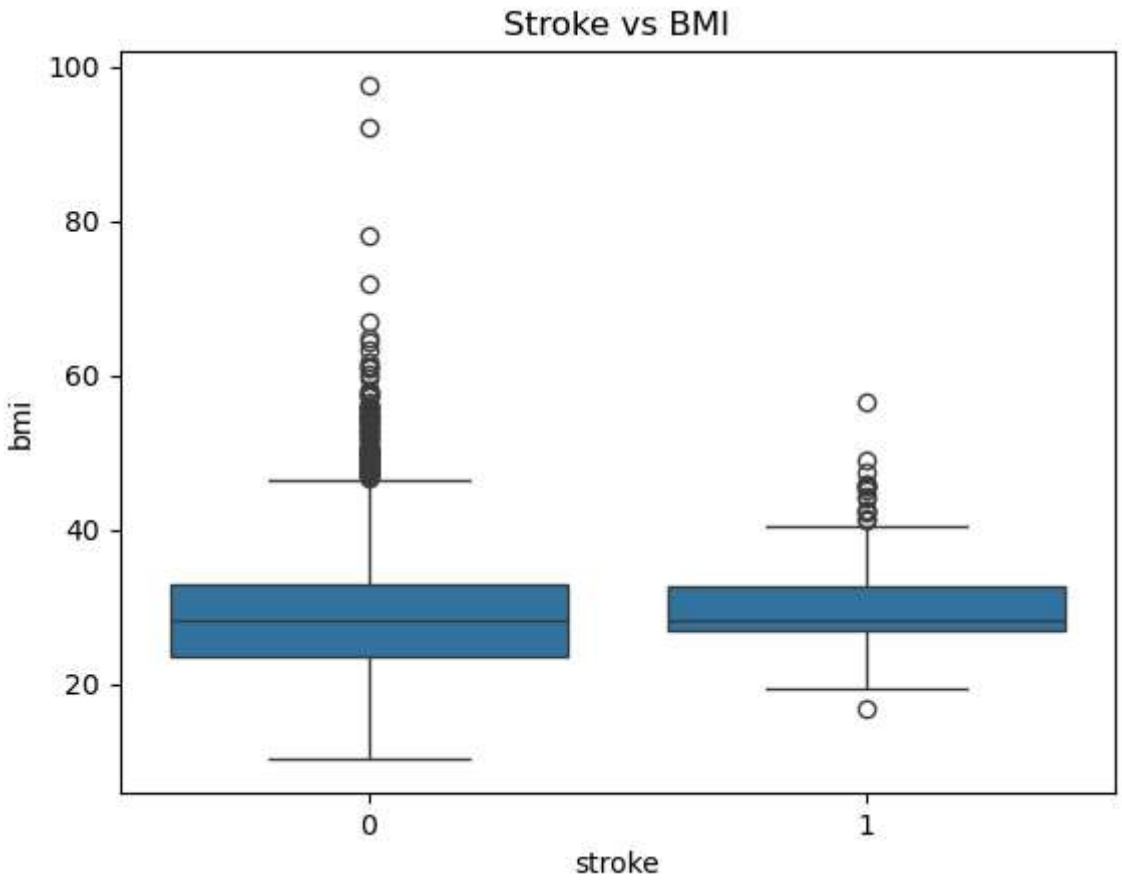


Interpretation: Age is a strong indicator of heart disease. People who suffer from heart disease are mostly in the older age group (probably 50+). You can expect age to be an important feature when predicting heart disease. Interpretation: While glucose level does show some influence on heart disease, it's not as strong a predictor as age. Still, higher glucose levels (possibly pre-diabetic/diabetic) may slightly increase heart disease risk. This feature could still help when used in combination with age, BMI, etc.

In [ ]:

In [24]:
```
sns.boxplot(x='stroke', y='age', data=df)
plt.title("Stroke vs Age")
plt.show()

sns.boxplot(x='stroke', y='bmi', data=df)
plt.title("Stroke vs BMI")
plt.show()
```


Stroke vs Age
80
60
40
20
0
age
0
1
stroke


Stroke vs BMI
100
80
60
40
20
bmi
0
1
stroke

In [ ]:

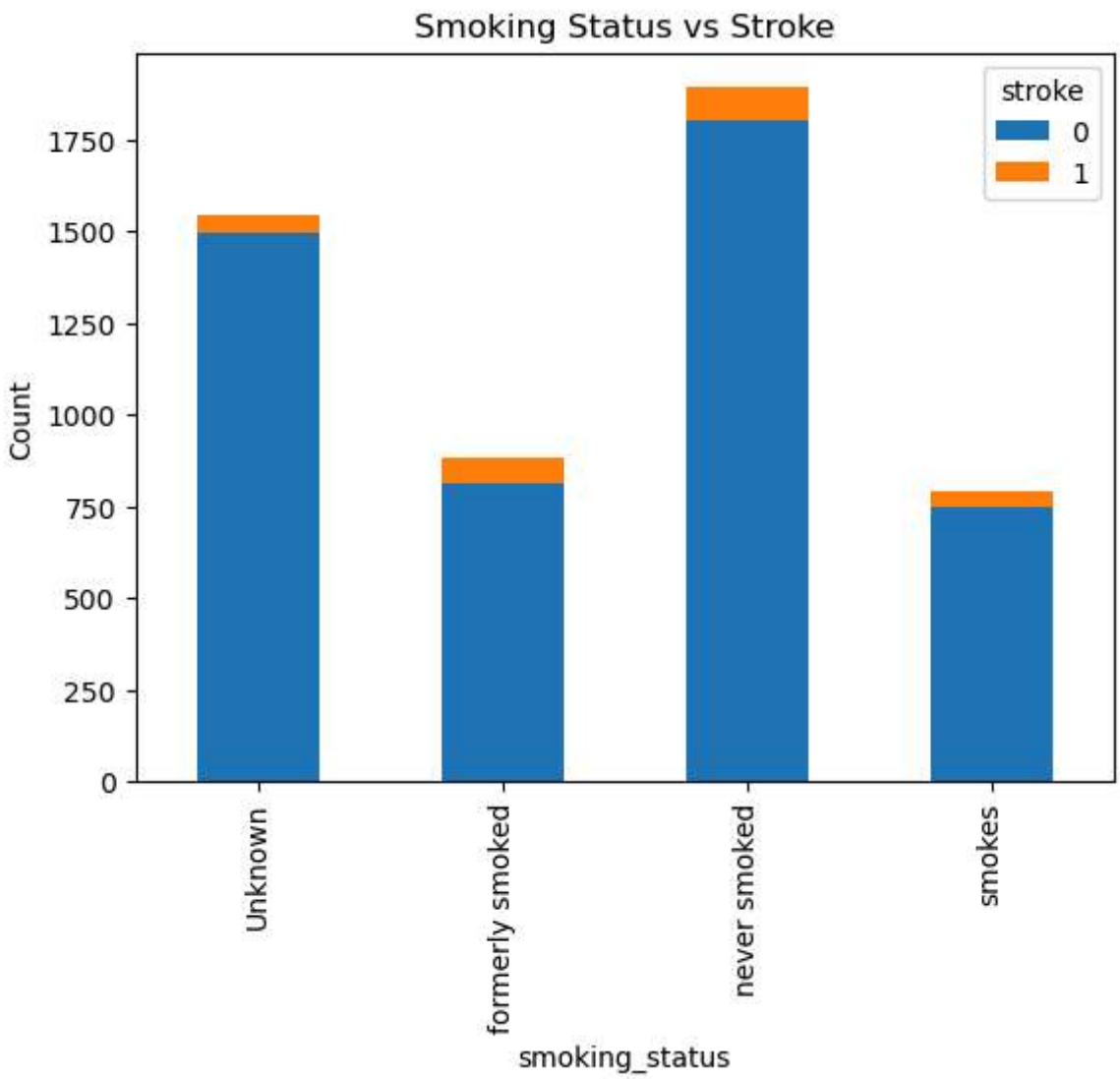
interpretation: People who had a stroke (stroke = 1) are mostly older. Their ages are usually around 60 to 80 years. People who did not have a stroke (stroke = 0) are of all age groups, including younger ones. So, older people have a higher chance of getting a stroke. Conclusion: Age is a strong factor — the risk of stroke increases with age. interpretation: People with stroke have a slightly higher BMI, but the difference is small. Both groups (with and without stroke) have a wide range of BMI values. This means that BMI alone is not a very strong factor for predicting stroke in this dataset. Conclusion: BMI might matter, but it's not as clearly related to stroke as age is.

In [ ]:

In [ ]:

smoking Status VS Stroke

In [25]:
```
pd.crosstab(df['smoking_status'], df['stroke']).plot(kind='bar', stacked=True)
plt.title("Smoking Status vs Stroke")
plt.ylabel("Count")
plt.show()
```



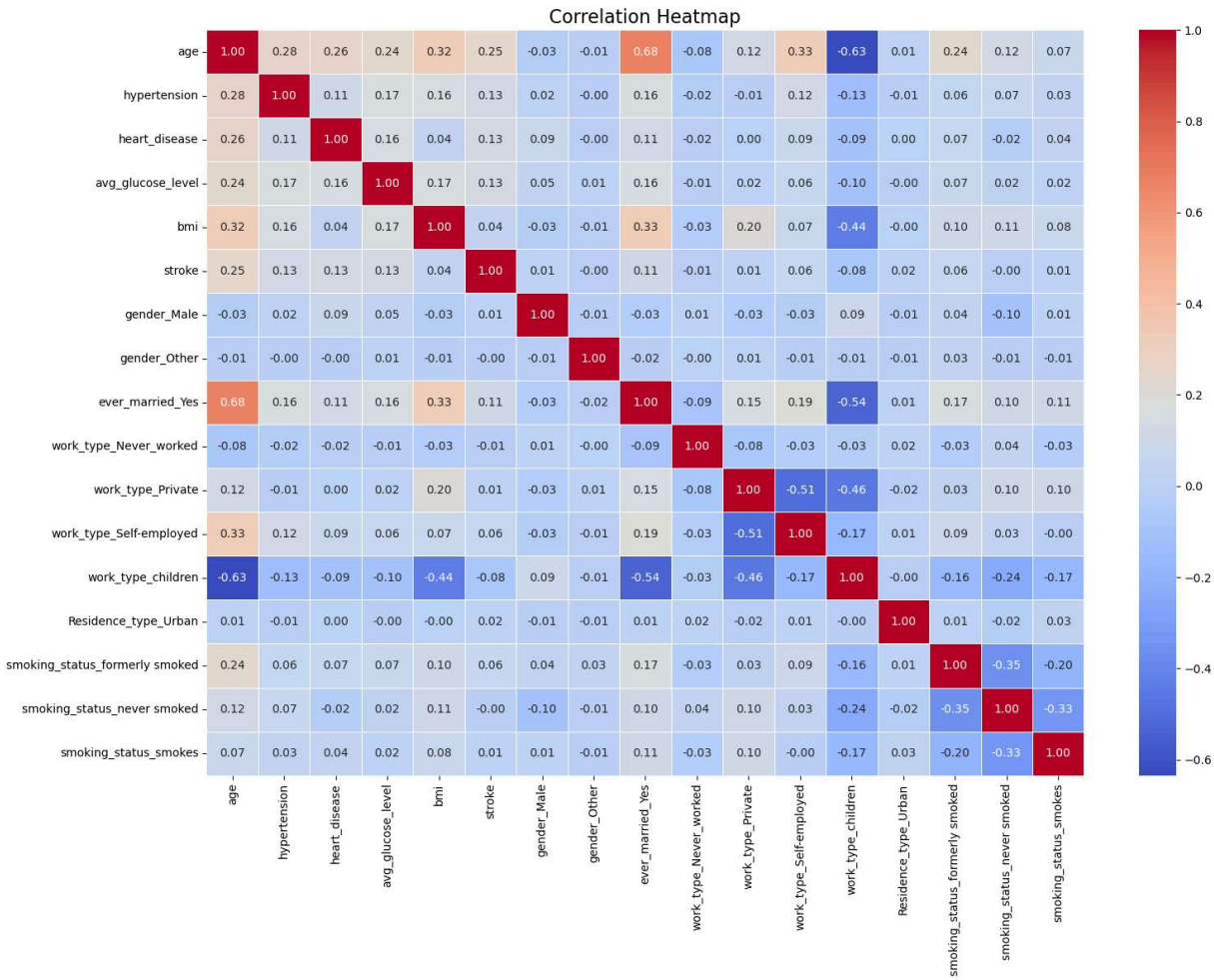
In [ ]:

Smoking—especially current or past smoking—appears to be associated with higher stroke risk. Never smokers have lower stroke counts, suggesting smoking is a risk factor for stroke in this dataset

In [ ]:

Correlation Matrix

In [26]:
```
# Encode categorical features
df_encoded = pd.get_dummies(df, drop_first=True)

# Plot heatmap
plt.figure(figsize=(16,12))  # Adjusted for better visibility
sns.heatmap(df_encoded.corr(), cmap="coolwarm", annot=True, fmt=".2f", linewidths=0
plt.title("Correlation Heatmap", fontsize=16)
plt.tight_layout()
plt.show()
```



It shows the linear relationship between each pair of features in the dataset. Values range from: +1 = Strong positive correlation -1 = Strong negative correlation 0 = No correlation

In [ ]:

Check for Class Imbalance

In [27]:
```
# Heart disease imbalance
print("Heart Disease Class Count:")
print(df['heart_disease'].value_counts(normalize=True))

# Stroke imbalance
print("Stroke Class Count:")
print(df['stroke'].value_counts(normalize=True))
```

```
Heart Disease Class Count:
heart_disease
0    0.945988
1    0.054012
Name: proportion, dtype: float64
Stroke Class Count:
stroke
0    0.951272
1    0.048728
Name: proportion, dtype: float64
```

In [ ]:

Final Cleaned Dataset Overview

In [28]:
```
print("Final dataset shape:", df.shape)
print("------------------------------------")
print("Final column types:\n", df.dtypes)
print("------------------------------------")
print("Any missing values left?:", df.isnull().sum().sum())
```

```
Final dataset shape: (5110, 11)
------------------------------------
Final column types:
 gender               category
age                   float64
hypertension            int64
heart_disease           int64
ever_married         category
work_type            category
Residence_type       category
avg_glucose_level     float64
bmi                   float64
smoking_status       category
stroke                  int64
dtype: object
------------------------------------
Any missing values left?: 0
```

In [ ]:

In [ ]:

Label Encoding

In [29]:
```
from sklearn.preprocessing import LabelEncoder
```

In [30]:
```
LE=LabelEncoder()
```

In [31]:
```
df_categorical=df.select_dtypes("category")
df_categorical
```

Out[31]:

	gender	ever_married	work_type	Residence_type	smoking_status
0	Male	Yes	Private	Urban	formerly smoked
1	Female	Yes	Self-employed	Rural	never smoked
2	Male	Yes	Private	Rural	never smoked
3	Female	Yes	Private	Urban	smokes
4	Female	Yes	Self-employed	Rural	never smoked
...	...	...	...	...	...
5105	Female	Yes	Private	Urban	never smoked
5106	Female	Yes	Self-employed	Urban	never smoked
5107	Female	Yes	Self-employed	Rural	never smoked
5108	Male	Yes	Private	Rural	formerly smoked
5109	Female	Yes	Govt_job	Urban	Unknown

5110 rows × 5 columns

In [32]:
```
for i in df_categorical:
    df_categorical[i]=LE.fit_transform(df_categorical[i])
df_categorical
```

Out[32]:

	gender	ever_married	work_type	Residence_type	smoking_status
0	1	1	2	1	1
1	0	1	3	0	2
2	1	1	2	0	2
3	0	1	2	1	3
4	0	1	3	0	2
...	...	...	...	...	...
5105	0	1	2	1	2
5106	0	1	3	1	2
5107	0	1	3	0	2
5108	1	1	2	0	1
5109	0	1	0	1	0

5110 rows × 5 columns

In [ ]:

In [ ]:

Scaling

In [33]:
```
df
```

Out[33]:

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type
0	Male	67.0	0	1	Yes	Private	Urban
1	Female	61.0	0	0	Yes	Self-employed	Rural
2	Male	80.0	0	1	Yes	Private	Rural
3	Female	49.0	0	0	Yes	Private	Urban
4	Female	79.0	1	0	Yes	Self-employed	Rural
...	...	...	...	...	...	...	...
5105	Female	80.0	1	0	Yes	Private	Urban
5106	Female	81.0	0	0	Yes	Self-employed	Urban
5107	Female	35.0	0	0	Yes	Self-employed	Rural
5108	Male	51.0	0	0	Yes	Private	Rural
5109	Female	44.0	0	0	Yes	Govt_job	Urban

5110 rows × 11 columns

In [34]:

```
df_Numerical=df.select_dtypes(["int64","float64"])
df_Numerical
```

Out[34]:

	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	28.1	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	28.1	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

5110 rows × 6 columns

In [ ]:

In [35]:
```
from sklearn.preprocessing import StandardScaler,MinMaxScaler
```

In [36]:
```
SS=MinMaxScaler()
```

In [37]:
```
scaled_numerical_array=SS.fit_transform(df_Numerical)
scaled_numerical_array
```

Out[37]:
```
array([[0.81689453, 0.        , 1.        , 0.80126489, 0.30126002,
        1.        ],
       [0.74365234, 0.        , 0.        , 0.67902317, 0.20389462,
        1.        ],
       [0.97558594, 0.        , 1.        , 0.23451205, 0.25429553,
        1.        ],
       ...,
       [0.42626953, 0.        , 0.        , 0.12865848, 0.2325315 ,
        0.        ],
       [0.62158203, 0.        , 0.        , 0.51320284, 0.17525773,
        0.        ],
       [0.53613281, 0.        , 0.        , 0.13922999, 0.18213058,
        0.        ]])
```

In [ ]:

In [38]:
```
scaled_numerical_df=pd.DataFrame(scaled_numerical_array,columns=df_Numerical.column
scaled_numerical_df
```

Out[38]:

	age	hypertension	heart_disease	avg_glucose_level	bmi	stroke
0	0.816895	0.0	1.0	0.801265	0.301260	1.0
1	0.743652	0.0	0.0	0.679023	0.203895	1.0
2	0.975586	0.0	1.0	0.234512	0.254296	1.0
3	0.597168	0.0	0.0	0.536008	0.276060	1.0
4	0.963379	1.0	0.0	0.549349	0.156930	1.0
...	...	...	...	...	...	...
5105	0.975586	1.0	0.0	0.132167	0.203895	0.0
5106	0.987793	0.0	0.0	0.323516	0.340206	0.0
5107	0.426270	0.0	0.0	0.128658	0.232532	0.0
5108	0.621582	0.0	0.0	0.513203	0.175258	0.0
5109	0.536133	0.0	0.0	0.139230	0.182131	0.0

5110 rows × 6 columns

In [ ]:

In [39]:

```
df2=pd.concat((scaled_numerical_df,df_categorical),axis=1)
df2
```

Out[39]:

	age	hypertension	heart_disease	avg_glucose_level	bmi	stroke	gender
0	0.816895	0.0	1.0	0.801265	0.301260	1.0	1
1	0.743652	0.0	0.0	0.679023	0.203895	1.0	0
2	0.975586	0.0	1.0	0.234512	0.254296	1.0	1
3	0.597168	0.0	0.0	0.536008	0.276060	1.0	0
4	0.963379	1.0	0.0	0.549349	0.156930	1.0	0
...	...	...	...	...	...	...	...
5105	0.975586	1.0	0.0	0.132167	0.203895	0.0	0
5106	0.987793	0.0	0.0	0.323516	0.340206	0.0	0
5107	0.426270	0.0	0.0	0.128658	0.232532	0.0	0
5108	0.621582	0.0	0.0	0.513203	0.175258	0.0	1
5109	0.536133	0.0	0.0	0.139230	0.182131	0.0	0

5110 rows × 11 columns

In [ ]:

Skewness Removal

In [40]:
```
from scipy.stats import skew
```

In [41]:
```
df2.select_dtypes(["int64","float64"]).columns
```

Out[41]:
```
Index(['age', 'hypertension', 'heart_disease', 'avg_glucose_level', 'bmi',
       'stroke', 'gender', 'ever_married', 'work_type', 'Residence_type',
       'smoking_status'],
      dtype='object')
```

In [ ]:

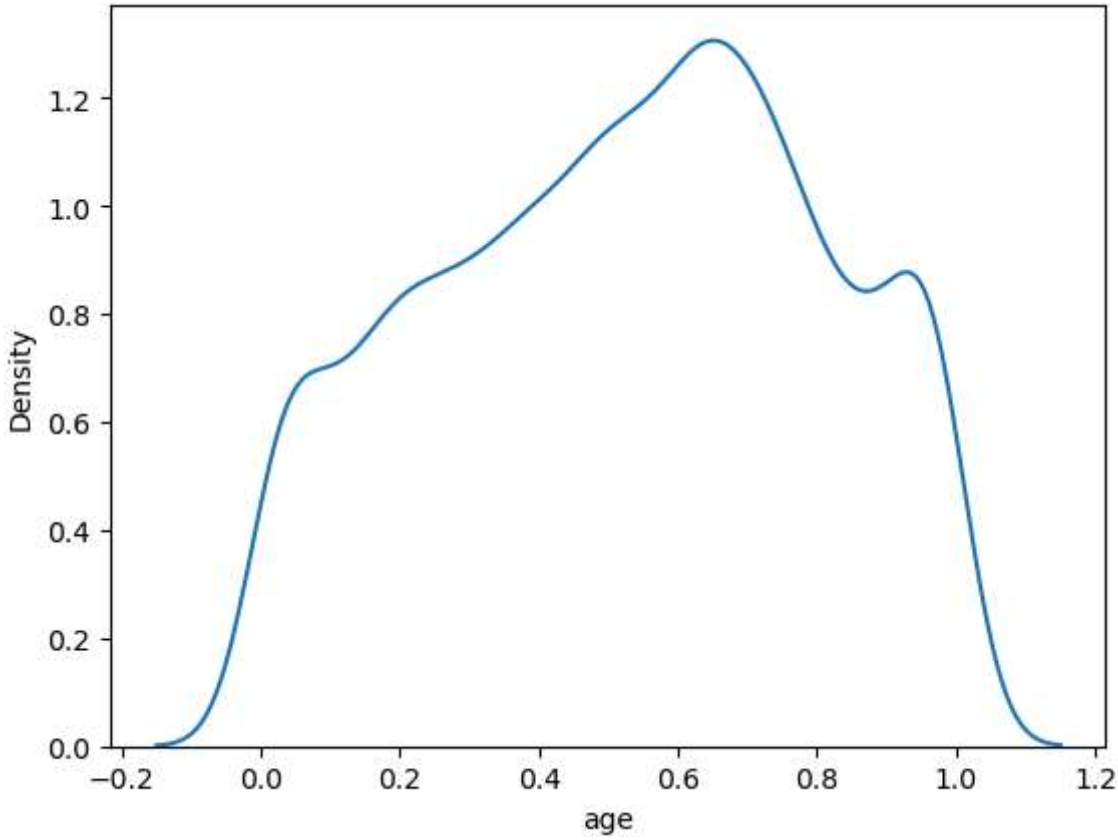
In [42]:
```
for i in df2.select_dtypes(["int64","float64"]).columns:
    print(f"Skewness of {i} is {round(df2[i].skew(),2)}\n")
```

```
Skewness of age is -0.14

Skewness of hypertension is 2.72

Skewness of heart_disease is 3.95

Skewness of avg_glucose_level is 1.57

Skewness of bmi is 1.09

Skewness of stroke is 4.19

Skewness of gender is 0.35

Skewness of ever_married is -0.66

Skewness of work_type is -0.31

Skewness of Residence_type is -0.03

Skewness of smoking_status is -0.04
```

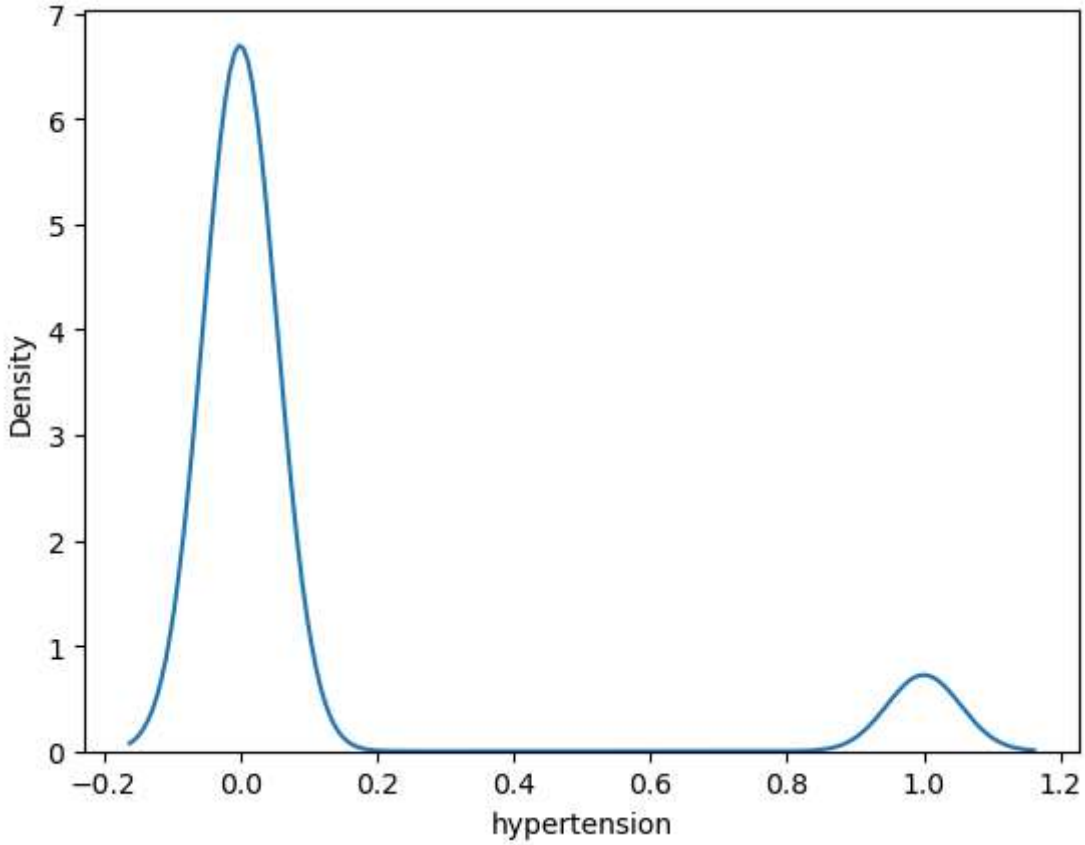
In [ ]:

In [43]:
```
for i in df2.select_dtypes(["int64","float64"]).columns:
    print(f"Skewness of {i} is {round(df2[i].skew(),2)}\n")
    sns.kdeplot(df2[i])
    plt.show()
```

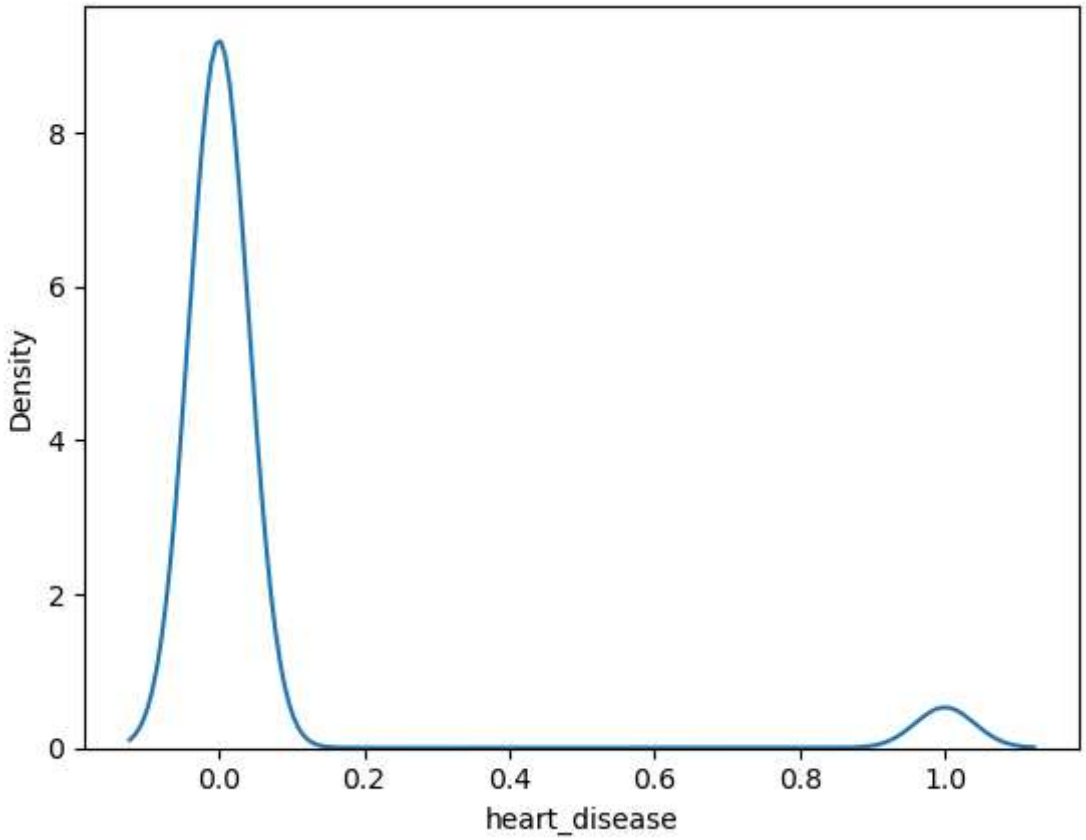
```
Skewness of age is -0.14
```



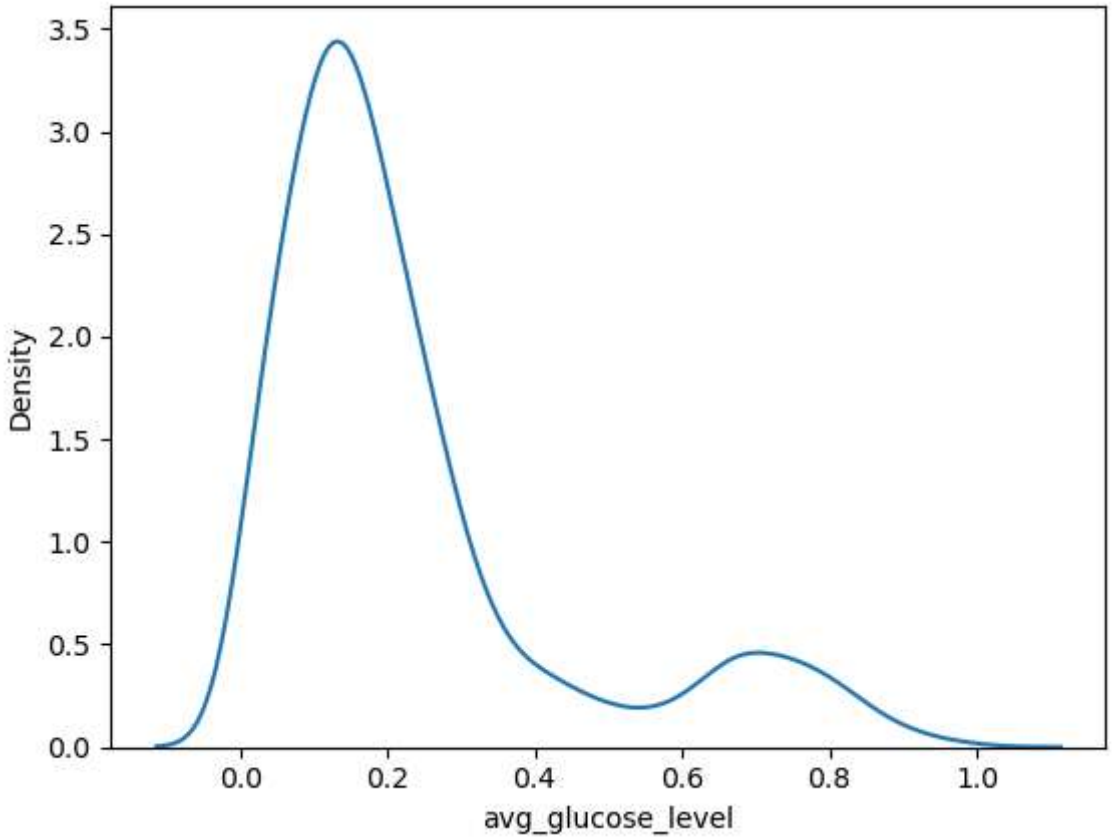

```
Skewness of hypertension is 2.72
```



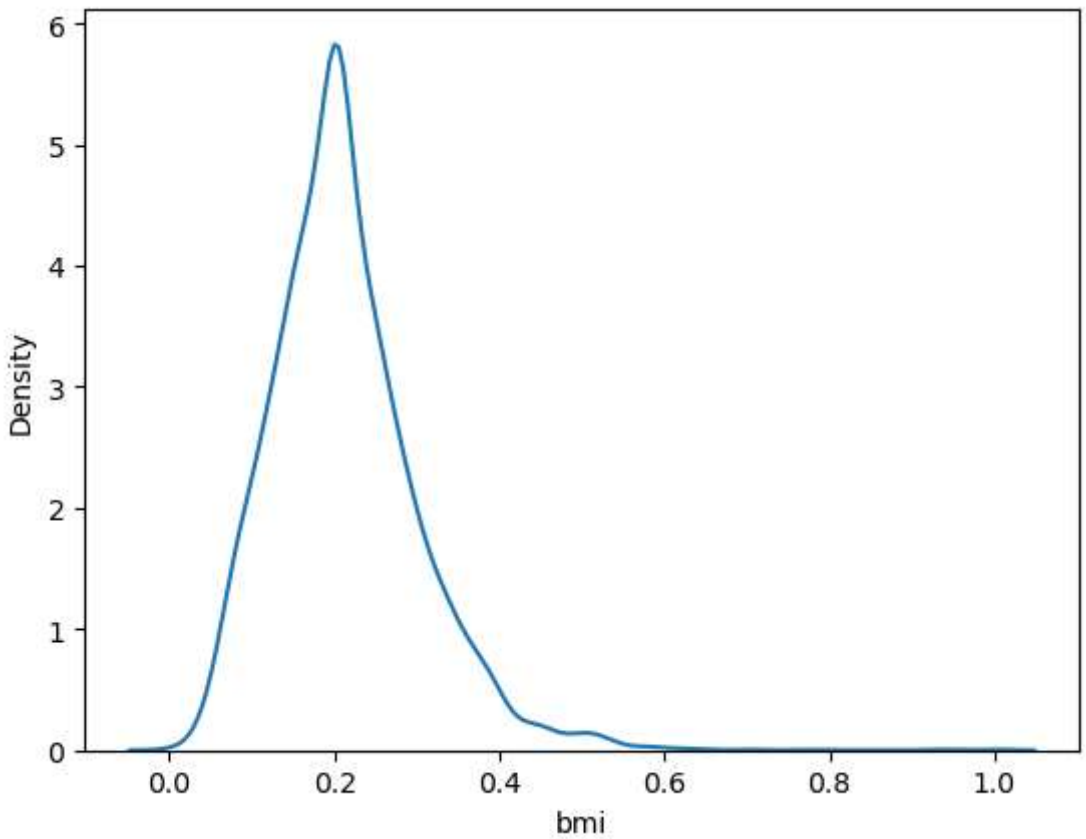

```
Skewness of heart_disease is 3.95
```



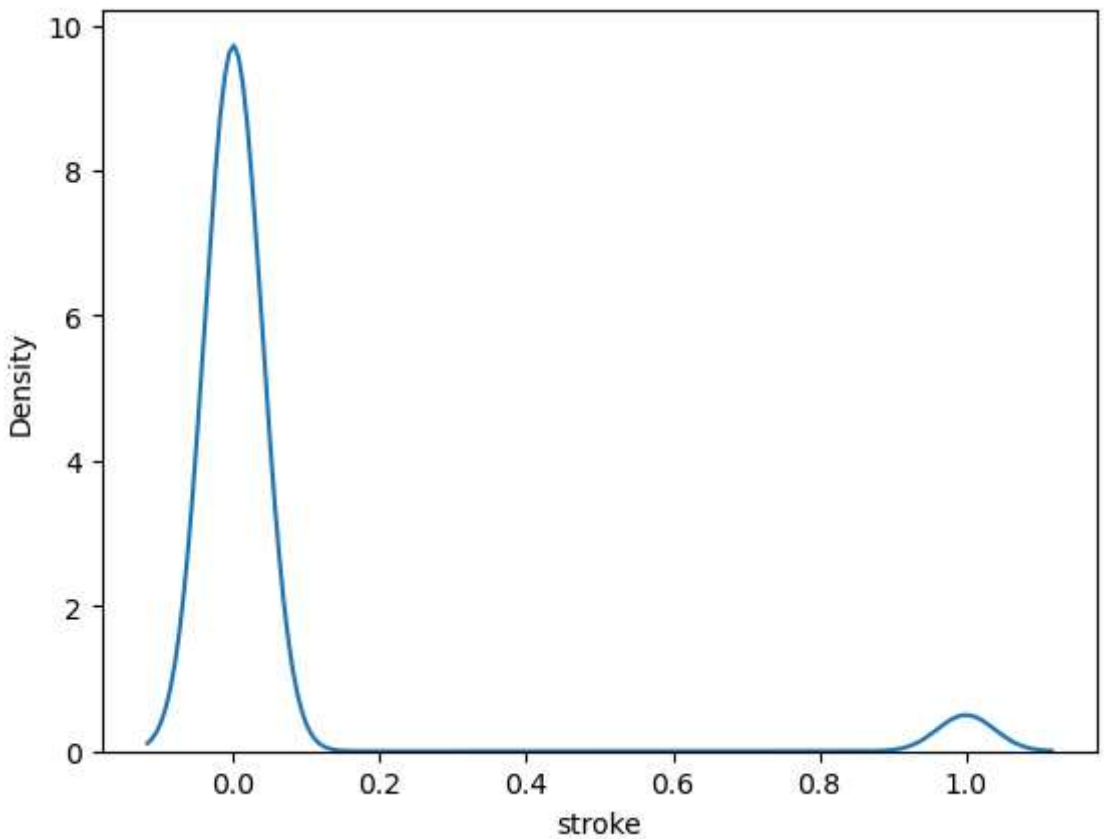

```
Skewness of avg_glucose_level is 1.57
```



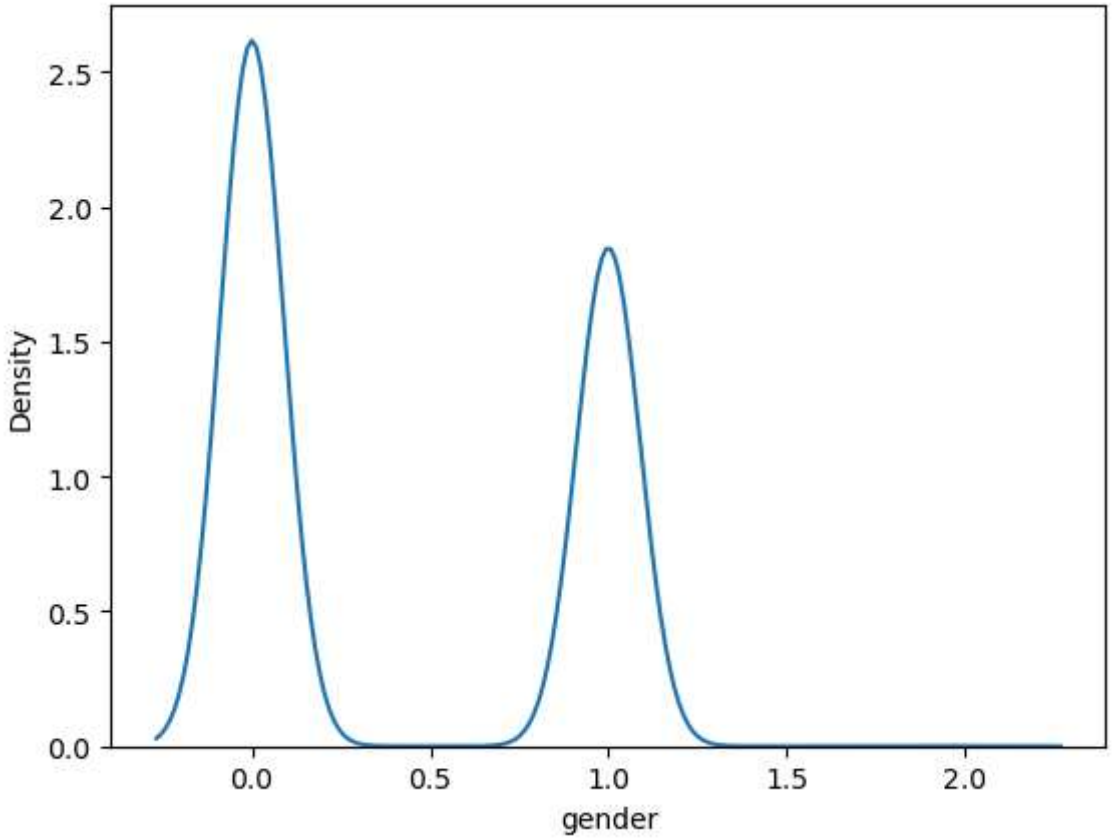

```
Skewness of bmi is 1.09
```



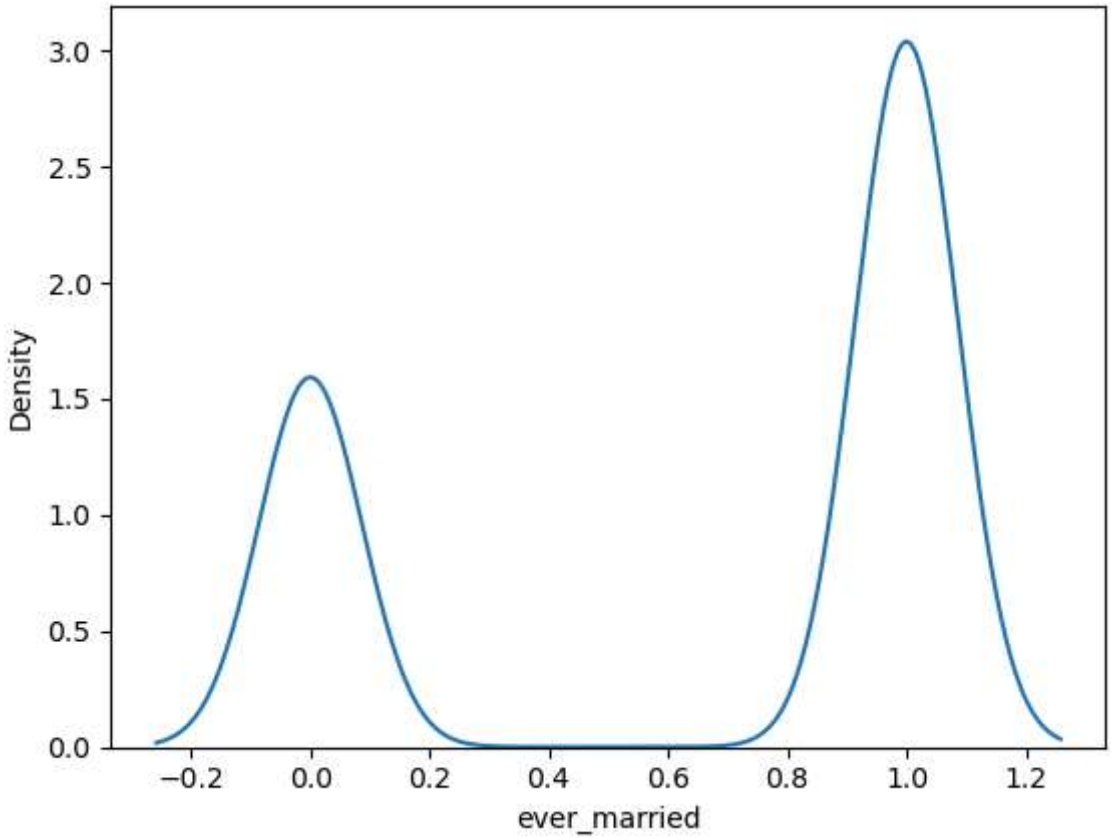

```
Skewness of stroke is 4.19
```



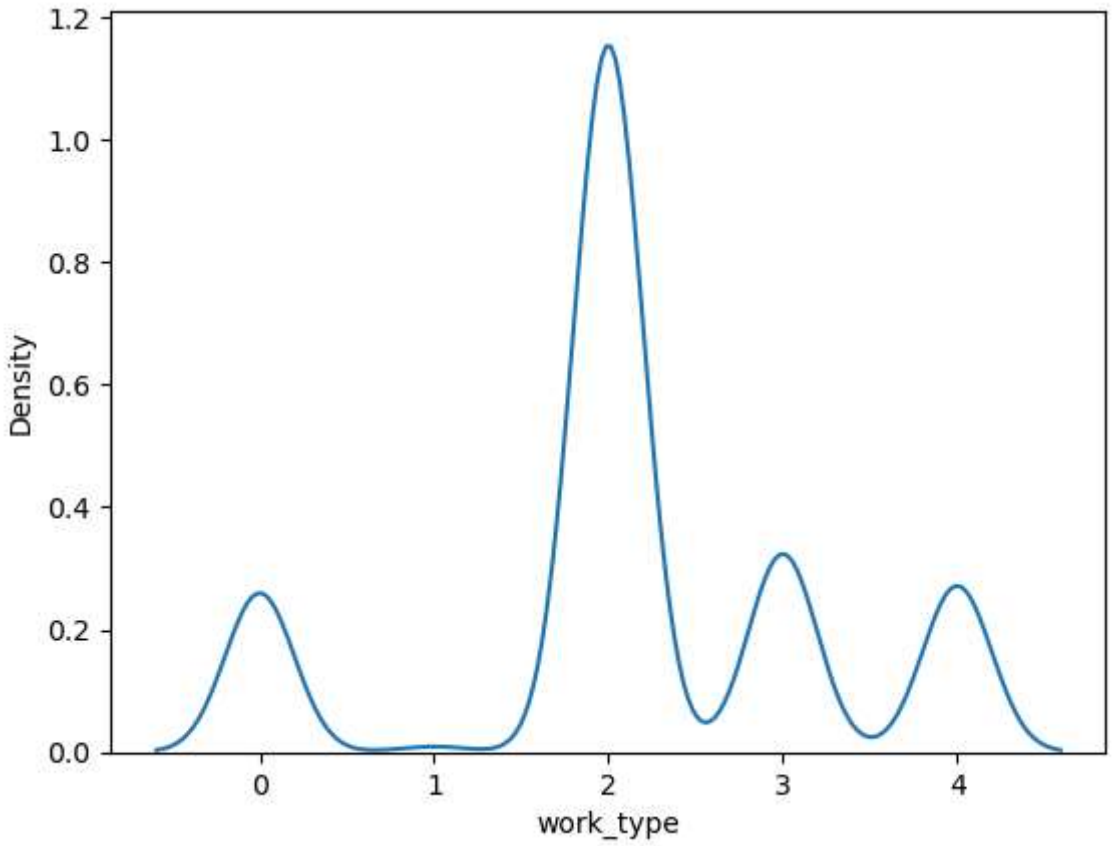

```
Skewness of gender is 0.35
```



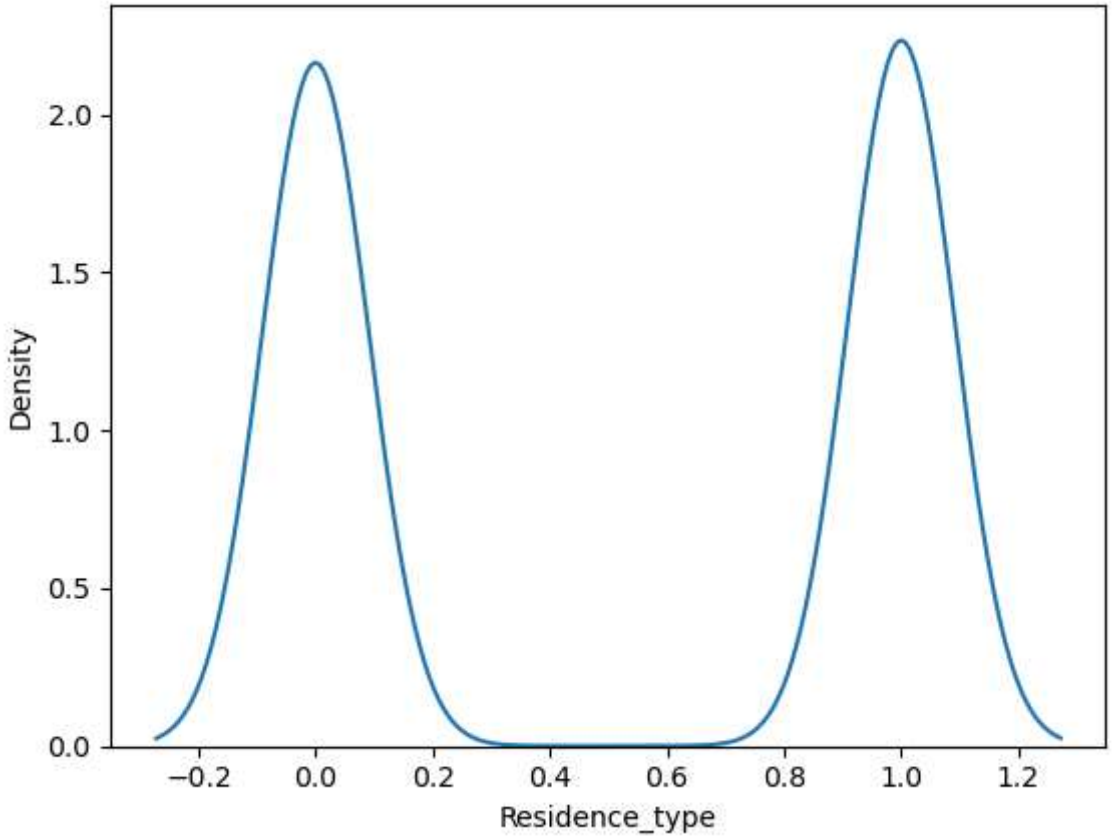

```
Skewness of ever_married is -0.66
```



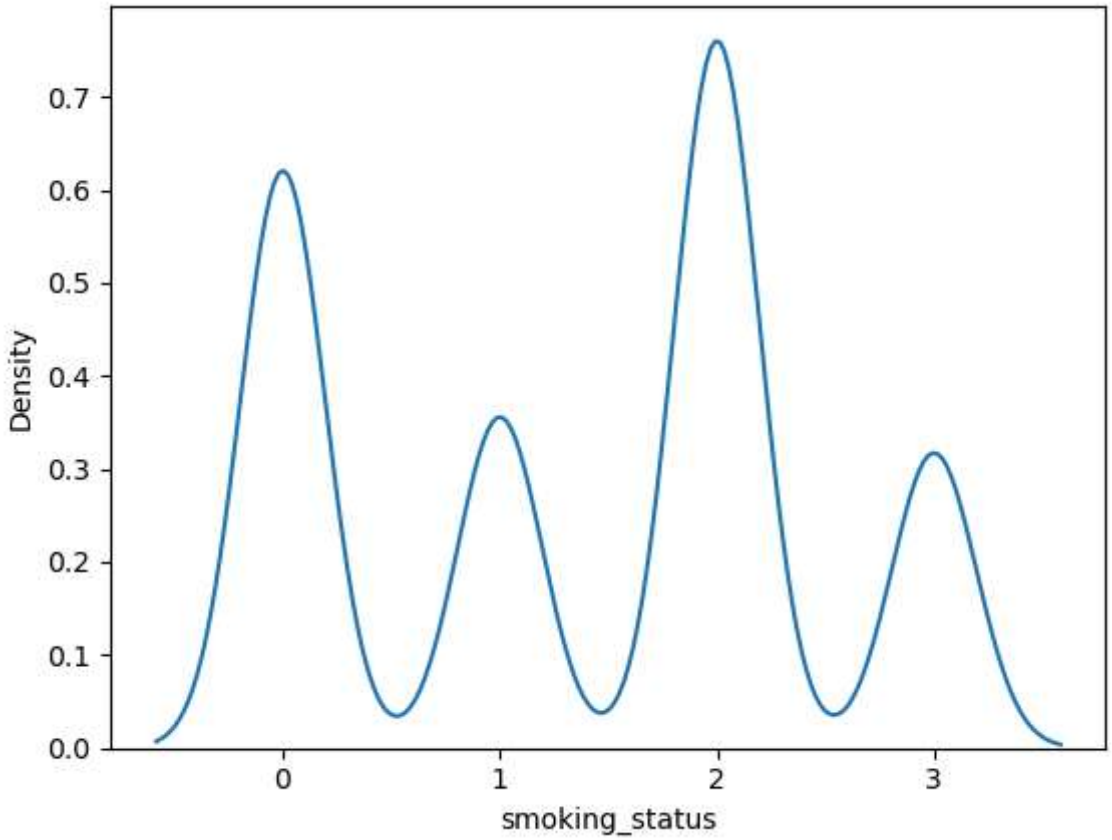

```
Skewness of work_type is -0.31
```




```
Skewness of Residence_type is -0.03
```




```
Skewness of smoking_status is -0.04
```



In [ ]:

In [ ]:

In [ ]:

In [ ]:

For Brain Stroke Prediction

In [ ]:

In [44]:
```
x=df2.drop('stroke', axis=1)
y=df2['stroke']
```

In [ ]:

In [45]:
```
x
```

Out[45]:

	age	hypertension	heart_disease	avg_glucose_level	bmi	gender	ever_mar
0	0.816895	0.0	1.0	0.801265	0.301260	1	
1	0.743652	0.0	0.0	0.679023	0.203895	0	
2	0.975586	0.0	1.0	0.234512	0.254296	1	
3	0.597168	0.0	0.0	0.536008	0.276060	0	
4	0.963379	1.0	0.0	0.549349	0.156930	0	
...	...	...	...	...	...	...	
5105	0.975586	1.0	0.0	0.132167	0.203895	0	
5106	0.987793	0.0	0.0	0.323516	0.340206	0	
5107	0.426270	0.0	0.0	0.128658	0.232532	0	
5108	0.621582	0.0	0.0	0.513203	0.175258	1	
5109	0.536133	0.0	0.0	0.139230	0.182131	0	

5110 rows × 10 columns

In [ ]:

In [46]:
```
y
```

Out[46]:
```
0       1.0
1       1.0
2       1.0
3       1.0
4       1.0
       ...
5105    0.0
5106    0.0
5107    0.0
5108    0.0
5109    0.0
Name: stroke, Length: 5110, dtype: float64
```

In [ ]:

In [ ]:

In [47]:
```
from sklearn.model_selection import train_test_split
```

In [48]:
```
xtrain, xtest, ytrain, ytest = train_test_split(x,y, test_size=0.15, random_state=4
```

In [ ]:

In [49]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.multioutput import MultiOutputClassifier
from sklearn.metrics import accuracy_score,classification_report
```

In [ ]:

In [ ]:

In [50]:
```
from sklearn.linear_model import LogisticRegression
```

In [51]:
```
LR=LogisticRegression()
LR.fit(xtrain,ytrain)
ypred=LR.predict(xtest)

accuracy = accuracy_score(ytest, ypred) * 100
print(f" Stroke Prediction Accuracy: {accuracy:.2f}%")
print("\n Classification Report:\n")
print(classification_report(ytest, ypred))
```

```
Stroke Prediction Accuracy: 93.87%

Classification Report:

              precision    recall  f1-score   support

         0.0       0.94      1.00      0.97       720
         1.0       0.00      0.00      0.00        47

    accuracy                           0.94       767
   macro avg       0.47      0.50      0.48       767
weighted avg       0.88      0.94      0.91       767
```

In [ ]:

In [52]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [53]:
```
DT=DecisionTreeClassifier()
DT.fit(xtrain,ytrain)
ypred=DT.predict(xtest)

accuracy = accuracy_score(ytest, ypred) * 100
print(f" Stroke Prediction Accuracy: {accuracy:.2f}%")
print("\n Classification Report:\n")
print(classification_report(ytest, ypred))
```

```
Stroke Prediction Accuracy: 91.53%

Classification Report:

              precision    recall  f1-score   support

         0.0       0.94      0.97      0.96       720
         1.0       0.20      0.13      0.16        47

    accuracy                           0.92       767
   macro avg       0.57      0.55      0.56       767
weighted avg       0.90      0.92      0.91       767
```

In [ ]:

In [54]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [55]:
```
KNN=KNeighborsClassifier()
KNN.fit(xtrain,ytrain)
ypred=KNN.predict(xtest)

accuracy = accuracy_score(ytest, ypred) * 100
print(f" Stroke Prediction Accuracy: {accuracy:.2f}%")
print("\n Classification Report:\n")
print(classification_report(ytest, ypred))
```

```
Stroke Prediction Accuracy: 93.87%

Classification Report:

              precision    recall  f1-score   support

         0.0       0.94      1.00      0.97       720
         1.0       0.50      0.02      0.04        47

    accuracy                           0.94       767
   macro avg       0.72      0.51      0.50       767
weighted avg       0.91      0.94      0.91       767
```

In [ ]:

In [56]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [57]:
```
RF=RandomForestClassifier()
RF.fit(xtrain,ytrain)
ypred=RF.predict(xtest)

accuracy = accuracy_score(ytest, ypred) * 100
print(f" Stroke Prediction Accuracy: {accuracy:.2f}%")
print("\n Classification Report:\n")
print(classification_report(ytest, ypred))
```

```
Stroke Prediction Accuracy: 94.00%

Classification Report:

              precision    recall  f1-score   support

         0.0       0.94      1.00      0.97       720
         1.0       1.00      0.02      0.04        47

    accuracy                           0.94       767
   macro avg       0.97      0.51      0.51       767
weighted avg       0.94      0.94      0.91       767
```

In [58]:
```
!pip install xgboost
```

```
Requirement already satisfied: xgboost in c:\users\piyush\anaconda3\lib\site-package
s (3.0.3)
Requirement already satisfied: numpy in c:\users\piyush\anaconda3\lib\site-packages
(from xgboost) (2.1.3)
Requirement already satisfied: scipy in c:\users\piyush\anaconda3\lib\site-packages
(from xgboost) (1.15.3)
```

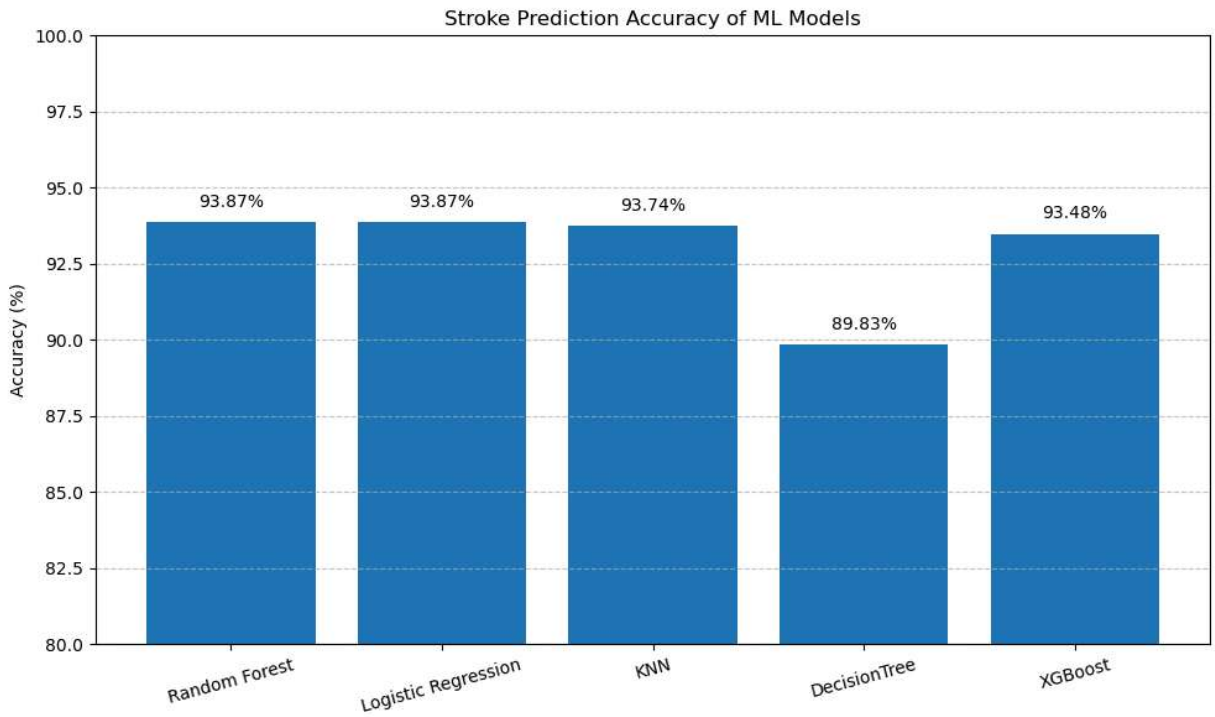
In [59]:
```
from xgboost import XGBClassifier

XGB = XGBClassifier(use_label_encoder=False, eval_metric='logloss')
XGB.fit(xtrain, ytrain)
ypred = XGB.predict(xtest)

accuracy = accuracy_score(ytest, ypred) * 100
print(f"XGBoost Accuracy: {accuracy:.2f}%")
print("\n Classification Report:\n")
print(classification_report(ytest, ypred))
```

```
XGBoost Accuracy: 93.61%

 Classification Report:

              precision    recall  f1-score   support

         0.0       0.94      0.99      0.97       720
         1.0       0.33      0.04      0.08        47

    accuracy                           0.94       767
   macro avg       0.64      0.52      0.52       767
weighted avg       0.90      0.94      0.91       767
```

In [60]:
```
rf_accuracy = 93.87
log_reg_accuracy = 93.87
knn_accuracy =93.74
DT_accuracy =89.83
xgb_accuracy = 93.48
```

In [61]:
```
import matplotlib.pyplot as plt

# Accuracy values (in %)
```

```
model_names = ['Random Forest', 'Logistic Regression', 'KNN', 'DecisionTree', 'XGBo
accuracies = [rf_accuracy, log_reg_accuracy, knn_accuracy, DT_accuracy, xgb_accurac

# Plot
plt.figure(figsize=(10,6))
plt.bar(model_names, accuracies)
plt.ylim(80, 100)
plt.ylabel('Accuracy (%)')
plt.title('Stroke Prediction Accuracy of ML Models')
plt.xticks(rotation=15)
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Annotate accuracy on top
for i, acc in enumerate(accuracies):
    plt.text(i, acc + 0.5, f"{acc:.2f}%", ha='center', fontsize=10)

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



INterpretation:- From the above observations we can see that RandomForest and logistic Regression are giving the best accuracy on the testing data as compared to others. So best Algorithm for the prediction of the stroke i would prefer to use any one of them. But i would use Random Forest for the prediction because: Random Forest usually performs better than Logistic Regression. Reason: Stroke prediction involves multiple health factors (age, hypertension, glucose level, BMI, etc.) that have complex, non-linear relationships. Radom Forest handles these non-linear patterns and feature interactions better. It also reduces overfitting by combining many decision trees. Logistic Regression works well if: Data is linearly separable (relationships are simple and straight-line boundaries). You want a very interpretable model (easy to explain coefficients to doctors/researchers).

In [ ]:

Make a predictive system

In [64]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
```

```
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.ensemble import RandomForestClassifier

df = pd.read_csv("Stroke_prediction.csv")
df = df.drop(['id'], axis=1)
df['bmi'].fillna(df['bmi'].median(), inplace=True)

X = df.drop("stroke", axis=1)
y = df["stroke"]

cat_cols = ['gender', 'ever_married', 'work_type', 'Residence_type', 'smoking_statu
num_cols = ['age', 'hypertension', 'heart_disease', 'avg_glucose_level', 'bmi']

# Pipeline for encoding + model
preprocess = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(handle_unknown='ignore'), cat_cols)
    ],
    remainder='passthrough'
)

model = Pipeline(steps=[
    ('preprocess', preprocess),
    ('classifier', RandomForestClassifier())
])

# Train
model.fit(X, y)


import joblib
joblib.dump(model, "model.pkl")
```

Out[64]: ['model.pkl']

In [65]:
```
df
```

Out[65]:

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type
0	Male	67.0	0	1	Yes	Private	Urban
1	Female	61.0	0	0	Yes	Self-employed	Rural
2	Male	80.0	0	1	Yes	Private	Rural
3	Female	49.0	0	0	Yes	Private	Urban
4	Female	79.0	1	0	Yes	Self-employed	Rural
...	...	...	...	...	...	...	...
5105	Female	80.0	1	0	Yes	Private	Urban
5106	Female	81.0	0	0	Yes	Self-employed	Urban
5107	Female	35.0	0	0	Yes	Self-employed	Rural
5108	Male	51.0	0	0	Yes	Private	Rural
5109	Female	44.0	0	0	Yes	Govt_job	Urban

5110 rows × 11 columns

In [66]:
```
from sklearn.metrics import accuracy_score

ypred = model.predict(X)
print("Training Accuracy:", accuracy_score(y, ypred))
```

```
Training Accuracy: 1.0
```

In [67]:
```
def stroke_prediction_system(model):
    print("\n===== Stroke Prediction System =====\n")

    user = {}

    user["age"] = float(input("Age: "))
    user["hypertension"] = int(input("Hypertension (0/1): "))
    user["heart_disease"] = int(input("Heart Disease (0/1): "))
    user["avg_glucose_level"] = float(input("Average Glucose Level: "))
    user["bmi"] = float(input("BMI: "))

    user["gender"] = input("Gender (Male/Female/Other): ")
    user["ever_married"] = input("Ever Married (Yes/No): ")
    user["work_type"] = input("Work Type (Private/Self-employed/Govt_job/children/N
    user["Residence_type"] = input("Residence (Urban/Rural): ")
    user["smoking_status"] = input("Smoking (formerly smoked/never smoked/smokes/Un
```

```
    df_input = pd.DataFrame([user])

    prediction = model.predict(df_input)[0]

    print("\n===== RESULT =====")
    if prediction == 1:
        print("⚠️ HIGH RISK OF STROKE")
    else:
        print("✅ NO STROKE RISK DETECTED")
    print("============================\n")
```

In [ ]:

In [68]:
```
stroke_prediction_system(model)
```

```
===== Stroke Prediction System =====

===== RESULT =====
⚠️ HIGH RISK OF STROKE
============================
```