STROKE PREDICTION USING MACHINE LEARNING

In [1]:

```
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings('ignore')


# Data Visualization Libraries,
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msv
from plotly.subplots import make_subplots
import plotly.graph_objects as go
from matplotlib.gridspec import GridSpec
from plotly.subplots import make_subplots
from plotly.offline import init_notebook_mode
from pywaffle import Waffle


# Machine Learning Libraries
from imblearn.over_sampling import SMOTE
from sklearn.metrics import precision_score,f1_score,recall_score,confusion_matrix
from sklearn.model_selection import train_test_split, RandomizedSearchCV, GridSearchCV
from sklearn.ensemble import RandomForestClassifier,GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier

# Artificial Neural Network Libraries
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.utils import plot_model
from sklearn.preprocessing import StandardScaler
```

In [2]:

```
# Import your data
data = pd.read_csv('healthcare-dataset-stroke-data.csv')
```

In [3]:

```
#View the first 5 rows in the dataset
data.head()
```

Out[3]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type
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 [4]:

```
# View last 5 rows in the dataset
data.tail()
```

Out[4]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_ty
5105	18234	Female	80.0	1	0	Yes	Private	Urt
5106	44873	Female	81.0	0	0	Yes	Self-employed	Urt
5107	19723	Female	35.0	0	0	Yes	Self-employed	Ru
5108	37544	Male	51.0	0	0	Yes	Private	Ru
5109	44679	Female	44.0	0	0	Yes	Govt_job	Urt

In [5]:

```
#get data description
data.describe()
```

Out[5]:

	id	age	hypertension	heart_disease	avg_glucose_level	
count	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	4909
mean	36517.829354	43.226614	0.097456	0.054012	106.147677	28
std	21161.721625	22.612647	0.296607	0.226063	45.283560	7
min	67.000000	0.080000	0.000000	0.000000	55.120000	10
25%	17741.250000	25.000000	0.000000	0.000000	77.245000	23
50%	36932.000000	45.000000	0.000000	0.000000	91.885000	28
75%	54682.000000	61.000000	0.000000	0.000000	114.090000	33
max	72940.000000	82.000000	1.000000	1.000000	271.740000	97

In [6]:

```python
fig = make_subplots(rows=1, cols=2)

fig.add_trace(go.Indicator(
                mode = "number",
                value = data.shape[0],
                number={'font':{'color': 'purple', 'size':75}},
                delta = {"reference": 400},
                title = {"text": "Rows <br><span style="
                                  "'font-size:0.7em;color:gray'></span>"},
                domain = {'y': [0, 1], 'x': [0, 0.2]}))
fig.add_trace(go.Indicator(
                mode = "number",
                value = data.shape[1],
                number={'font':{'color': 'purple', 'size':75}},
                delta = {"reference": 400},
                title = {"text": "Columns <br><span style="
                                  "'font-size:0.6em;color:gray'></span>"},
                domain = {'y': [0, 0], 'x': [1, 1]}))
```

Rows	Columns
5110	12

In [6]:

```
# Created a function to get necessary information from the data set in a dataframe
def get_data_info():
    dataset_info = pd.DataFrame(index=data.columns)
    dataset_info['Data_type'] = data.dtypes
    dataset_info['Total Value'] = data.count()
    dataset_info['Null_count'] = data.isnull().sum()
    dataset_info['Unique_count'] = data.nunique()
    return dataset_info
```

In [7]:

```
get_data_info()
```

Out[7]:

	Data_type	Total Value	Null_count	Unique_count
id	int64	5110	0	5110
gender	object	5110	0	3
age	float64	5110	0	104
hypertension	int64	5110	0	2
heart_disease	int64	5110	0	2
ever_married	object	5110	0	2
work_type	object	5110	0	5
Residence_type	object	5110	0	2
avg_glucose_level	float64	5110	0	3979
bmi	float64	4909	201	418
smoking_status	object	5110	0	4
stroke	int64	5110	0	2

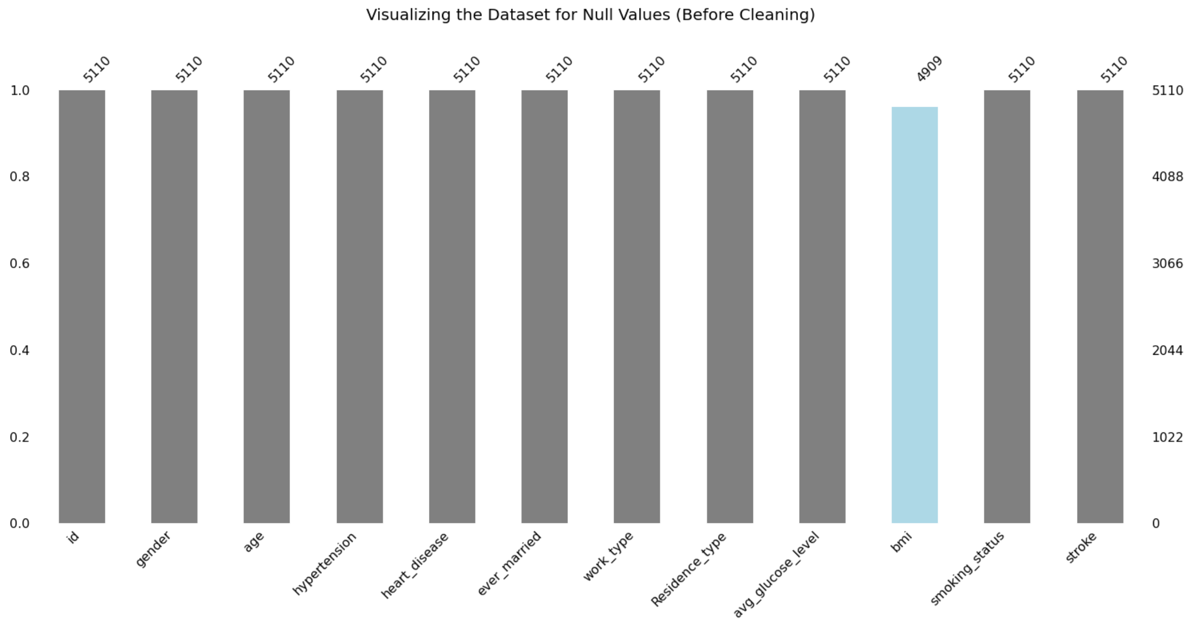
It is now easy to view missing data in all fields, their unique values and datatypes.

As seen above, the dataset only has missing values in the BMI column. Let's visualize that.

DATA CLEANING

In [8]:

```
MissingValuesColors = []

for i in data.columns:
    if data[i].isna().sum() != 0:
        MissingValuesColors.append('lightblue')
    else:
        MissingValuesColors.append('gray')

msv.bar(data, color=MissingValuesColors)
plt.title('Visualizing the Dataset for Null Values (Before Cleaning)', size=20, y=1.15
plt.savefig("Visualizations\DataFrameDirty.png")
plt.show()
```



In [9]:

```
data.gender.value_counts()
```

Out[9]:

```
Female    2994
Male      2115
Other        1
Name: gender, dtype: int64
```

In [10]:

```
# Drop the others category because it is too small to consider.
```

In [11]:

```
#Drop row with others gender.
data = data[data.gender != 'Other']
```

In [12]:

```
#Drop the missing values because the values are less than 5% of the total value
data = data.dropna()
```

In [13]:

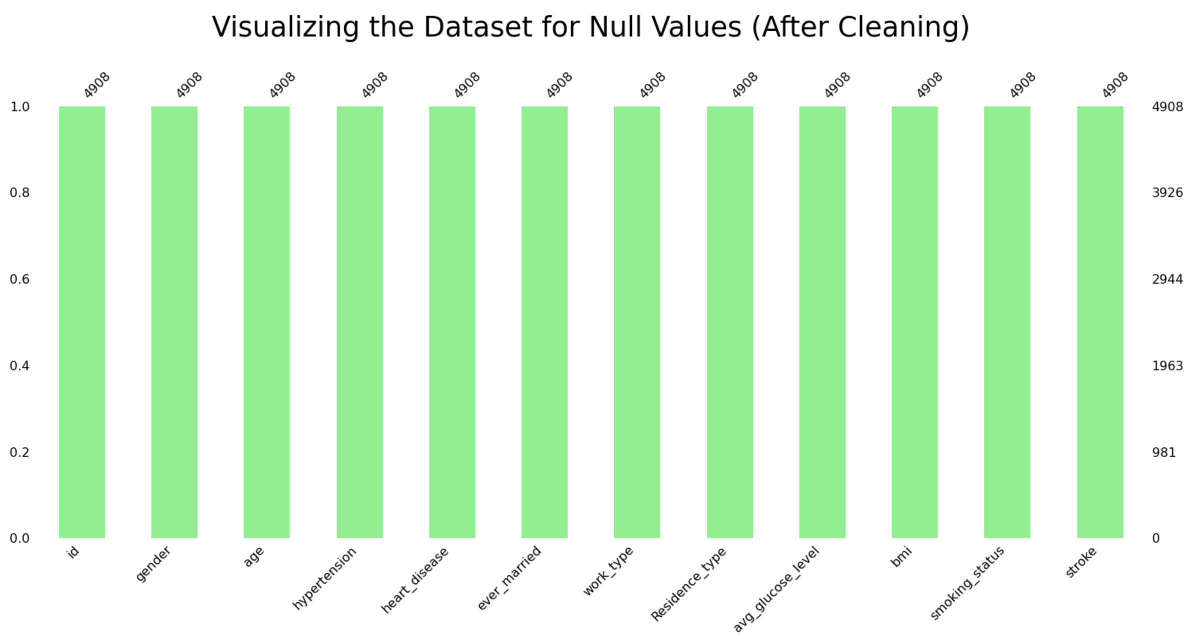
```
get_data_info()
```

Out[13]:

	Data_type	Total Value	Null_count	Unique_count
id	int64	4908	0	4908
gender	object	4908	0	2
age	float64	4908	0	104
hypertension	int64	4908	0	2
heart_disease	int64	4908	0	2
ever_married	object	4908	0	2
work_type	object	4908	0	5
Residence_type	object	4908	0	2
avg_glucose_level	float64	4908	0	3851
bmi	float64	4908	0	418
smoking_status	object	4908	0	4
stroke	int64	4908	0	2

In [14]:

```
MissingValuesColors = []

for i in data.columns:
    if data[i].isna().sum() != 0:
        MissingValuesColors.append('lightblue')
    else:
        MissingValuesColors.append('lightgreen')

msv.bar(data, color=MissingValuesColors)
plt.title('Visualizing the Dataset for Null Values (After Cleaning)', size=35, y=1.15)
plt.savefig("Visualizations\DataframeCleaned.png")
plt.show()
```



We have successfully removed all NA values.

In [15]:

```
# Age is seen as a float instead of Int, hence
# Convert Age to int
data['age'] = data['age'].astype(int)
get_data_info()
```

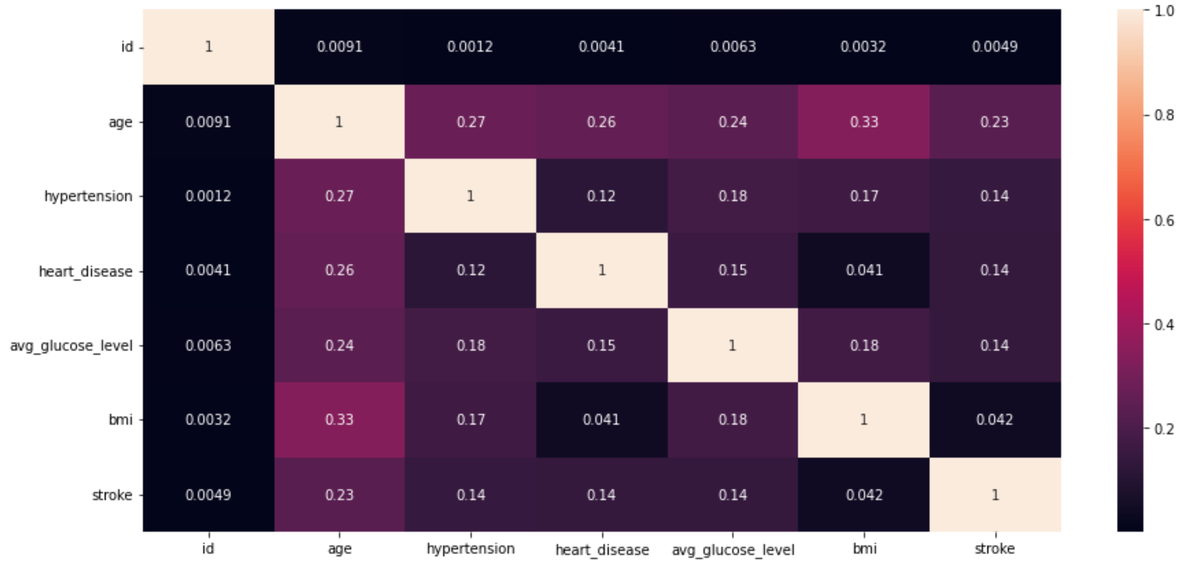
Out[15]:

	Data_type	Total Value	Null_count	Unique_count
id	int64	4908	0	4908
gender	object	4908	0	2
age	int32	4908	0	83
hypertension	int64	4908	0	2
heart_disease	int64	4908	0	2
ever_married	object	4908	0	2
work_type	object	4908	0	5
Residence_type	object	4908	0	2
avg_glucose_level	float64	4908	0	3851
bmi	float64	4908	0	418
smoking_status	object	4908	0	4
stroke	int64	4908	0	2

DATA VISUALIZATION

In [16]:

```
plt.figure(figsize=(15,7))
sns.heatmap(data.corr(),annot=True)
plt.savefig("Visualizations\heatmap.png")
plt.show()
```



In [17]:

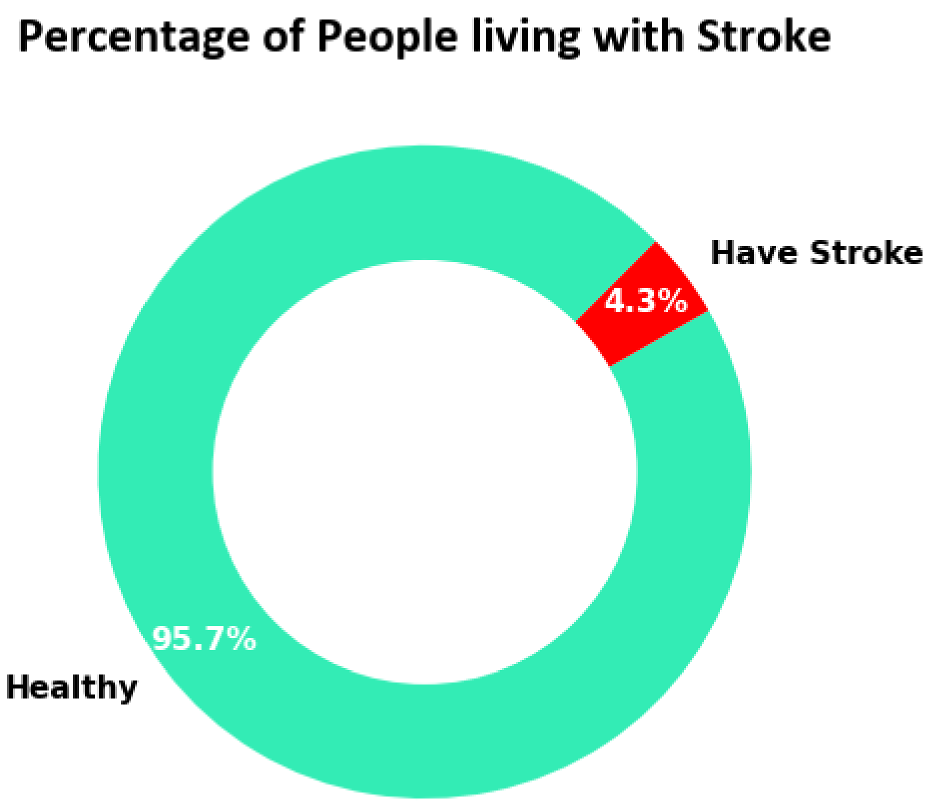
```
#From the Dataset, Let's calculate the percentage of peoople that have stroke and do nc
data.stroke.value_counts()
```

Out[17]:

```
0    4699
1     209
Name: stroke, dtype: int64
```

In [18]:

```
palette2 = ['#33ECB5','#ff0000']

colors = ('#E2F11C','#E3460A')
plt.figure(figsize=(10,7.5))
label = ['Healthy','Have Stroke']
patches, texts, pcts = plt.pie(data.stroke.value_counts(),
                               labels=label,
                               colors=[palette2[0],'#ff0000'],
                               pctdistance=0.85,
                               shadow=False,
                               startangle=45,
                               autopct='%1.1f%%',
                               textprops={'fontsize': 15.5,
                                          'weight': 'bold'
                                          })
plt.setp(pcts, color='white')

hfont = {'fontname':'calibri', 'weight': 'bold'}
plt.title('Percentage of People living with Stroke', size=25, **hfont)

centre_circle = plt.Circle((0,0),0.65,fc='white')
fig = plt.gcf()
fig.gca().add_artist(centre_circle)
plt.savefig("Visualizations\PieChart.png")
plt.show()
```



In [19]:

```
GenderGroupWithoutStroke = data.groupby(['gender','stroke']).count()['id'][[0,2]]
GenderGroupWithoutStroke
```

Out[19]:

```
gender  stroke
Female  0         2777
Male    0         1922
Name: id, dtype: int64
```

In [20]:

```
GenderGroupWithStroke = data.groupby(['gender','stroke']).count()['id'][[1,3]]
GenderGroupWithStroke
```

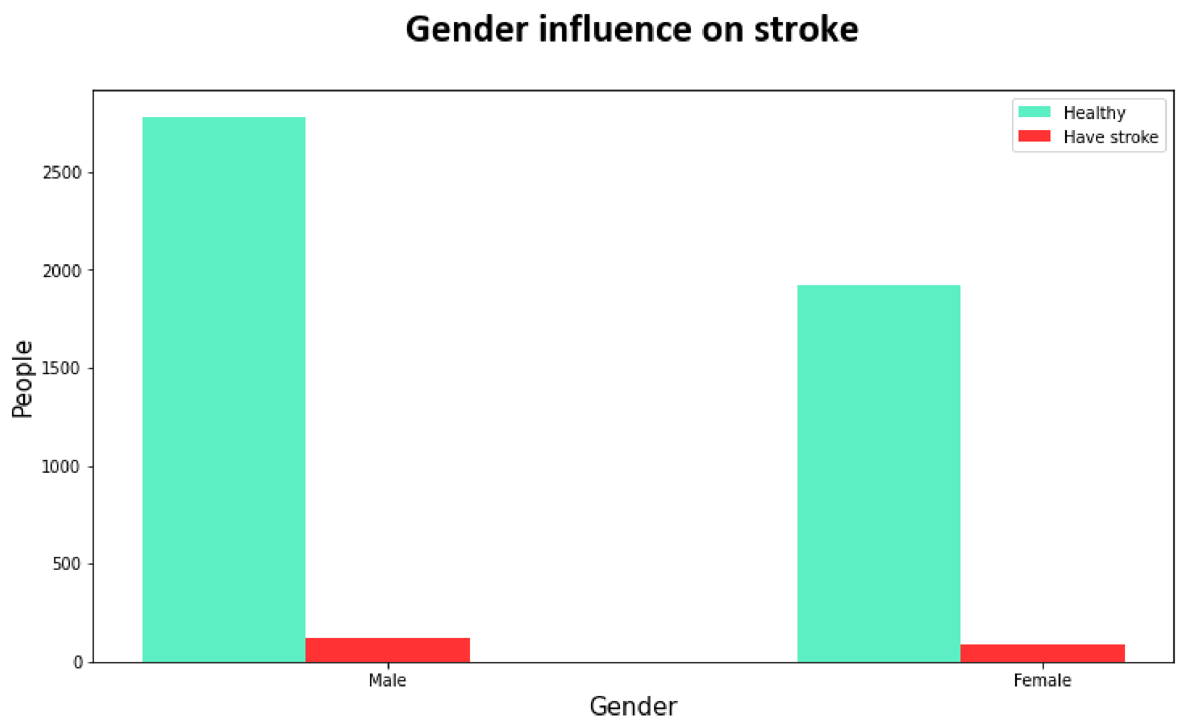
Out[20]:

```
gender  stroke
Female  1         120
Male    1          89
Name: id, dtype: int64
```

Assumption 1: MALE ARE MORE SUSCEPTIBLE TO STROKE DUE TO HIGH WORK RELATED STRESS

In [21]:

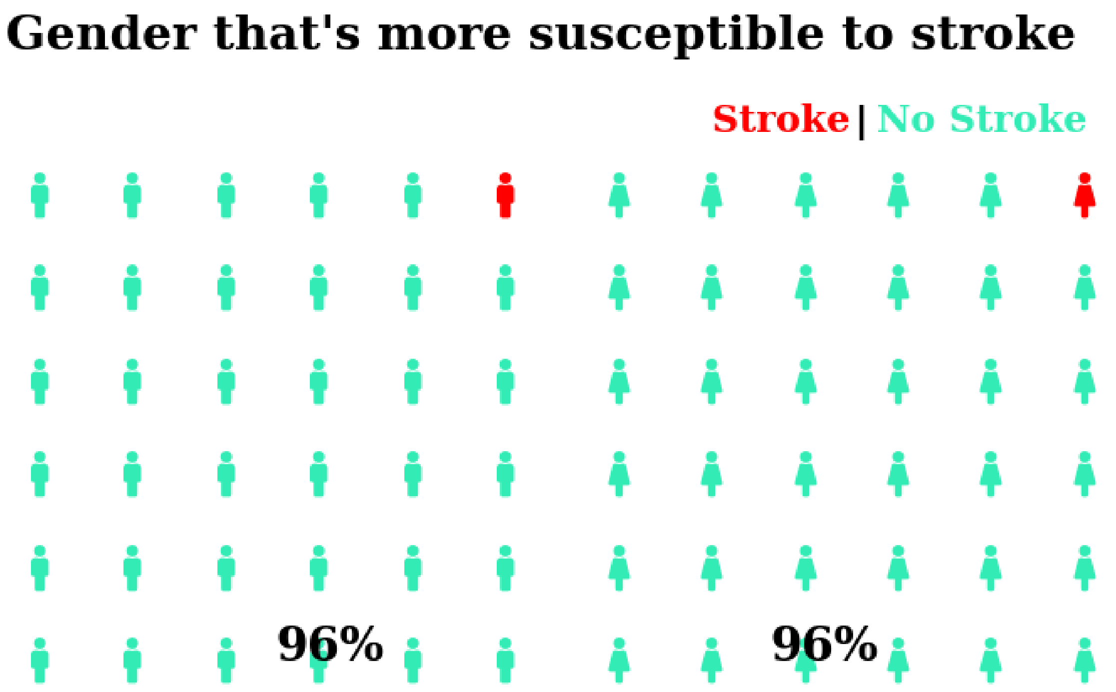
```
n_groups = 2

# create plot
plt.figure(figsize=(12,6.5))
indexx = np.arange(n_groups)
bar_width = 0.25
opacity = 0.8

rects1 = plt.bar(indexx, GenderGroupWithoutStroke, bar_width,
alpha=opacity,
color= palette2[0],
label='Healthy')

rects2 = plt.bar(indexx + bar_width, GenderGroupWithStroke, bar_width,
alpha=opacity,
color='#ff0000',
label='Have stroke')

plt.xlabel('Gender', size=15)
plt.ylabel('People',size=15)
plt.title('Gender influence on stroke\n',size=25, **hfont)
plt.xticks(indexx + bar_width, ('Male', 'Female'))
plt.legend()
plt.savefig("Visualizations\GenderInfluence.png")
plt.show()
```



In [22]:

```
#Let's visualize the data by finding the percentage of people Living with stroke and w
stroke_gen = data[data['stroke'] == 1]['gender'].value_counts()
healthy_gen = data[data['stroke'] == 0]['gender'].value_counts()

female = data['gender'].value_counts().values[0]
male =  data['gender'].value_counts().values[1]

stroke_female = int(round (stroke_gen.values[0] / female * 100, 0))
stroke_male = int(round( stroke_gen.values[1] / male *100, 0))
healthy_female = int(round(healthy_gen.values[0] / female * 100, 0))
healthy_male = int(round(healthy_gen.values[1] / male *100, 0))

female_per = int(round(female/(female+male) * 100, 0))
male_per = int(round(male/(female+male)* 100, 0))

fig = plt.figure(FigureClass = Waffle,
                 constrained_layout = True,
                 figsize = (7,7),
                 facecolor = '#fff',dpi = 100,

                 plots = {'121':
                          {
                           'rows':6,
                           'columns': 6,
                           'values' : [healthy_male,stroke_male],
                            'colors' : [palette2[0],'#ff0000'],
                              'vertical' : True,
                              'interval_ratio_y': 0.1,
                              'interval_ratio_x': 0.1,
                              'icons' : 'male',
                              'icon_legend': False,
                              'icon_size':20,
                              'plot_anchor':'C',
                              'alpha':0.1
                          },

                          '122' :
                          {
                            'rows': 6,
                            'columns':6,
                            'values':[healthy_female,stroke_female],
                              'colors' : [palette2[0],'#ff0000'],
                              'vertical': True,
                              'interval_ratio_y': 0.1,
                              'interval_ratio_x': 0.1,
                              'icons' : 'female',
                              'icon_legend' :False,
                              'icon_size':20,
                              'plot_anchor':'C',
                              'alpha':0.1

                           }
                         },

)
fig.text(0., 0.8, "Gender that's more susceptible to stroke", {'font':'Serif', 'size':
fig.text(0.23, 0.28, '{}%'.format(healthy_male), {'font':'Serif', 'size':20,'weight':'
fig.text(0.65, 0.28, '{}%'.format(healthy_female), {'font':'Serif', 'size':20,'weight'
fig.text(0.6,0.73, 'Stroke ', {'font': 'Serif','weight':'bold','Size': '16','weight':'
```

```
fig.text(0.72,0.73, '|', {'color':'black' , 'size':'16', 'weight': 'bold'})
fig.text(0.74,0.73, 'No Stroke', {'font': 'Serif','weight':'bold', 'Size': '16','style
plt.savefig("Visualizations\GenderProportion.png")
fig.show()
```

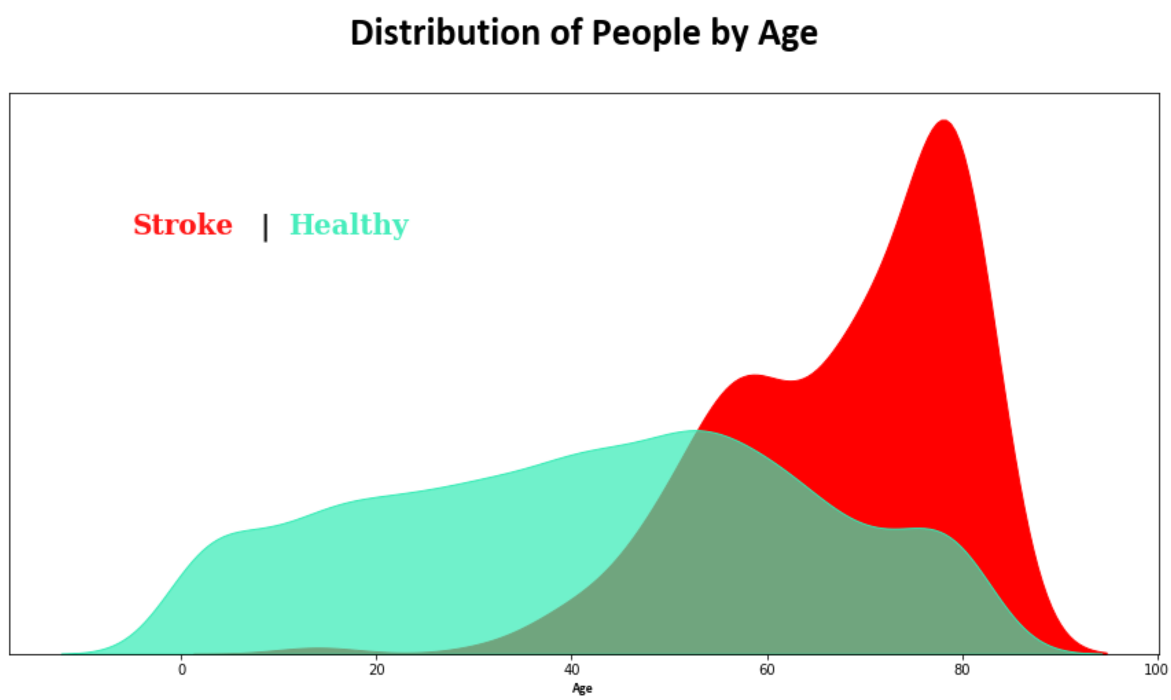


ℹ From the above diagram, it shows that the assumption is wrong. Being a male doesn't mean you're more susceptible to stroke.

? Question 1) DOES AGE HAVE AN IMPACT ON STROKE?

In [23]:

```
fig = plt.figure(figsize=(15, 7.5))
ax = fig.add_subplot(111)
plt.title('Distribution of People by Age\n', size=28, **hfont)
ax.grid(False)
ax.axes.get_yaxis().set_visible(False)
ax.text(-5, 0.03, 'Stroke', {'font': 'Serif',
                             'size': '20',
                             'weight': 'bold',
                             'color': '#ff0000'}, alpha=0.9)

ax.text(8, 0.03, '|', {'font': 'Serif',
                       'size': '20',
                       'weight': 'bold',
                       'color': 'black'}, alpha=0.9)

ax.text(11, 0.03, 'Healthy', {'font': 'Serif',
                              'size': '20',
                              'weight': 'bold',
                              'color': palette2[0]}, alpha=0.9)

sns.kdeplot(data=data[data.stroke == 1],
            x='age', shade=True, ax=ax, color='#ff0000', alpha=1)
sns.kdeplot(data=data[data.stroke == 0],
            x='age', shade=True, ax=ax, color=palette2[0], alpha=0.7)
plt.xlabel('Age', **hfont)
plt.savefig("Visualizations\DistributionOfPeopleByAge.png")
plt.show()
```



In [24]:

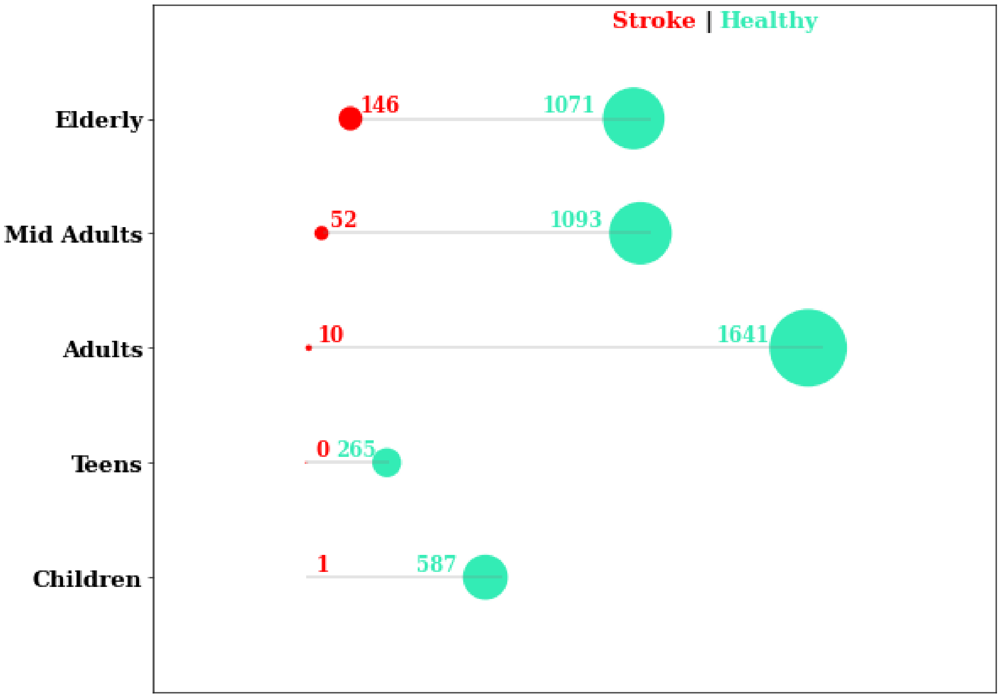
```
#Categorizing my BMI, Age and Glucose Columns into categorical values using range.
#Categories used
#Age: 0-12   :  Children,    BMI: 0-18  : Underweight      GlucoseLevel:   0-89
#     13-17  :  Teens,            19-24 : Ideal                             90-159
#     18-44  :  Adults            25-30 : Overweight                        160-229
#     45-59  :  Mid Adults        30-50 : Obesity                           230-500
#     60-150 :  Elderly

data['bmi_cat'] = pd.cut(data['bmi'], bins = [0, 19, 25,30,50], labels = ['Underweight
data['age_cat'] = pd.cut(data['age'], bins = [0,13,18, 45,60,150], labels = ['Children
data['glucose_cat'] = pd.cut(data['avg_glucose_level'], bins = [0,90,160,230,500], labe
```

In [25]:

```
# Using the Categories created above, Let's Visualize those that have Stroke with the A

fig = plt.figure(figsize = (24,10), dpi = 60)

gs = fig.add_gridspec(10,24)
gs.update(wspace = 1, hspace = 0.05)

ax1 = fig.add_subplot(gs[1:10,13:]) #dumbbell plot
stroke_age = data[data['stroke'] == 1].age_cat.value_counts()
healthy_age = data[data['stroke'] == 0].age_cat.value_counts()

ax1.hlines(y = ['Children', 'Teens', 'Adults', 'Mid Adults', 'Elderly'], xmin = [644,27
          xmax = [1,1,11,59,177], color = 'grey',**{'linewidth':0.5})


sns.scatterplot(y = stroke_age.index, x = stroke_age.values, s = stroke_age.values*2, c
sns.scatterplot(y = healthy_age.index, x = healthy_age.values, s = healthy_age.values*2

ax1.axes.get_xaxis().set_visible(False)
ax1.set_xlim(xmin = -500, xmax = 2250)
ax1.set_ylim(ymin = -1,ymax = 5)

ax1.set_yticklabels( labels = ['Children', 'Teens', 'Adults', 'Mid Adults', 'Elderly'],

ax1.text(0,5.8, 'Impact of age on stroke? \n' ,{'font': 'Serif', 'Size': '20','weight'
ax1.text(1000,4.8, '\nStroke ', {'font': 'Serif','weight':'bold','Size': '16','weight'
ax1.text(1300,4.8, '\n|', {'color':'black' , 'size':'16', 'weight': 'bold'})
ax1.text(1350,4.8, '\nHealthy', {'font': 'Serif','weight':'bold', 'Size': '16','style'
ax1.text(-550,5., 'Age has a significant impact on stroke, and clearly seen that stroke
        {'font':'Serif', 'size':'16','color': 'black'})

ax1.text(stroke_age.values[0] + 30,4.05, stroke_age.values[0], {'font':'Serif', 'Size'
ax1.text(healthy_age.values[2] - 300,4.05, healthy_age.values[2], {'font':'Serif', 'Si

ax1.text(stroke_age.values[1] + 30,3.05, stroke_age.values[1], {'font':'Serif', 'Size'
ax1.text(healthy_age.values[1] - 300,3.05, healthy_age.values[1], {'font':'Serif', 'Si

ax1.text(stroke_age.values[2] + 30,2.05, stroke_age.values[2], {'font':'Serif', 'Size'
ax1.text(healthy_age.values[0] - 300,2.05, healthy_age.values[0], {'font':'Serif', 'Si

ax1.text(stroke_age.values[4] + 30,1.05, stroke_age.values[4], {'font':'Serif', 'Size'
ax1.text(healthy_age.values[4] - 170,1.05, healthy_age.values[4], {'font':'Serif', 'Si

ax1.text(stroke_age.values[3] + 30,0.05, stroke_age.values[3], {'font':'Serif', 'Size'
ax1.text(healthy_age.values[3] - 225,0.05, healthy_age.values[3], {'font':'Serif', 'Si
plt.savefig("Visualizations\ImpactofAgeonStroke.png")
plt.show()
```

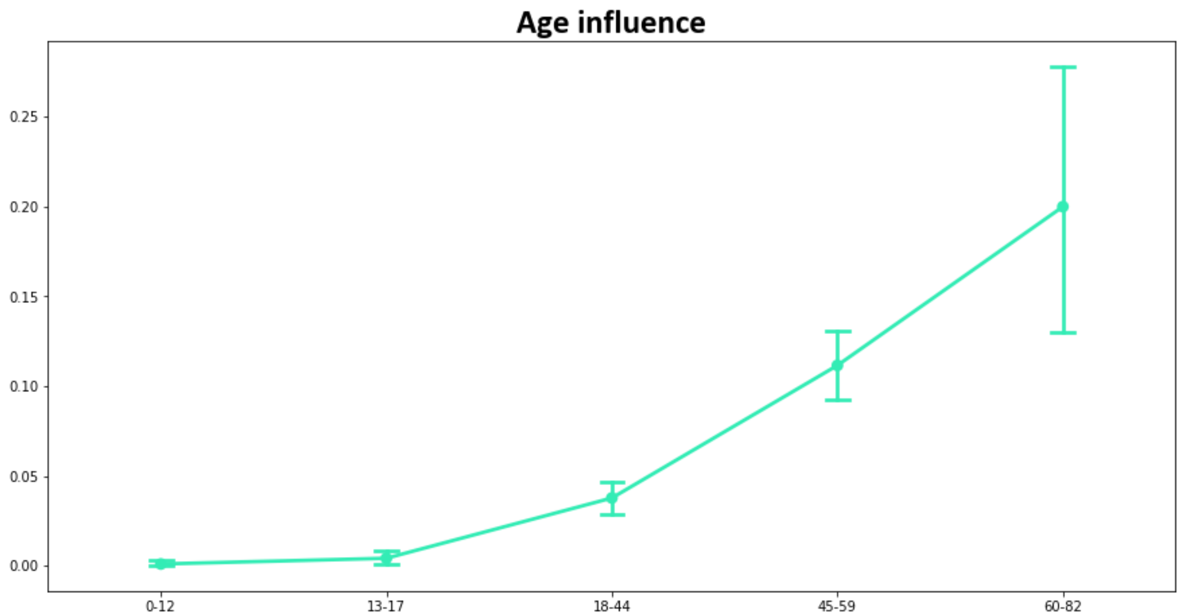
Impact of age on stroke?

Age has a significant impact on stroke, and clearly seen that stroke numbers are highest for elderly people and mid age adults, where as negligible for younger people.



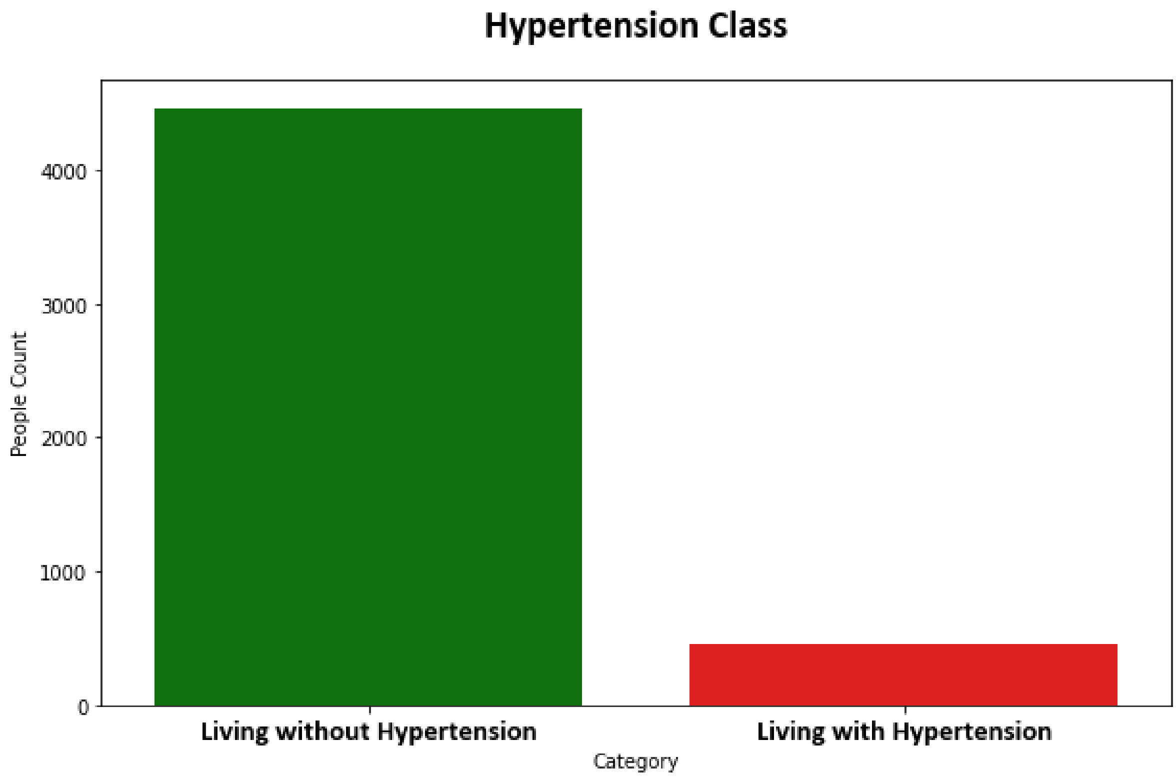
In [26]:

```python
label = ['0-12','13-17','18-44', '45-59',f'60-{round(data.age.max())}']

def plot_age(data, Column_Name):

    AgeData = data[[Column_Name, 'stroke']]
    AgeData[Column_Name] = pd.cut(AgeData[Column_Name],
                                  bins=[0, 20, 40, 60, 80, 100],
                                  labels=label)

    color = np.random.choice(palette2, 1)[0]
    plt.figure(figsize=(15, 7.5))
    plot = sns.pointplot(x=Column_Name, y='stroke',
                 dodge=0.1, capsize=.1, data=AgeData, color=color)
    plot.set_title(f'Age influence', fontsize=25, **hfont)
    plot.set(xlabel=None, ylabel=None)
    plt.savefig("Visualizations\AgeInfluence.png")
    plt.show()
plot_age(data, 'age')
```



In [27]:

```
plt.figure(figsize=(10, 6))
HypertensiveDistribution = sns.countplot(x=data.hypertension,palette=(['green','red'])
HypertensiveDistribution.set_title('Hypertension Class',fontsize=20, y=1.05, **hfont)
HypertensiveDistribution.set(xlabel='Category', ylabel='People Count')
plt.grid(False)
HypertensiveDistribution.set_xticklabels(['Living without Hypertension', 'Living with H
plt.savefig("Visualizations\HypertensionClass.png")
plt.show()
```



In [28]:

```
data.smoking_status.unique()
```

Out[28]:

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

In [29]:

```
data.columns
```

Out[29]:

```
Index(['id', 'gender', 'age', 'hypertension', 'heart_disease', 'ever_marrie
d',
       'work_type', 'Residence_type', 'avg_glucose_level', 'bmi',
       'smoking_status', 'stroke', 'bmi_cat', 'age_cat', 'glucose_cat'],
      dtype='object')
```

In [30]:

```
HypertensionGroupWithoutStroke = data.groupby(['hypertension','stroke']).count()['id']
HypertensionGroupWithoutStroke
```

Out[30]:

```
hypertension  stroke
0             0         4308
              1          149
Name: id, dtype: int64
```

In [31]:

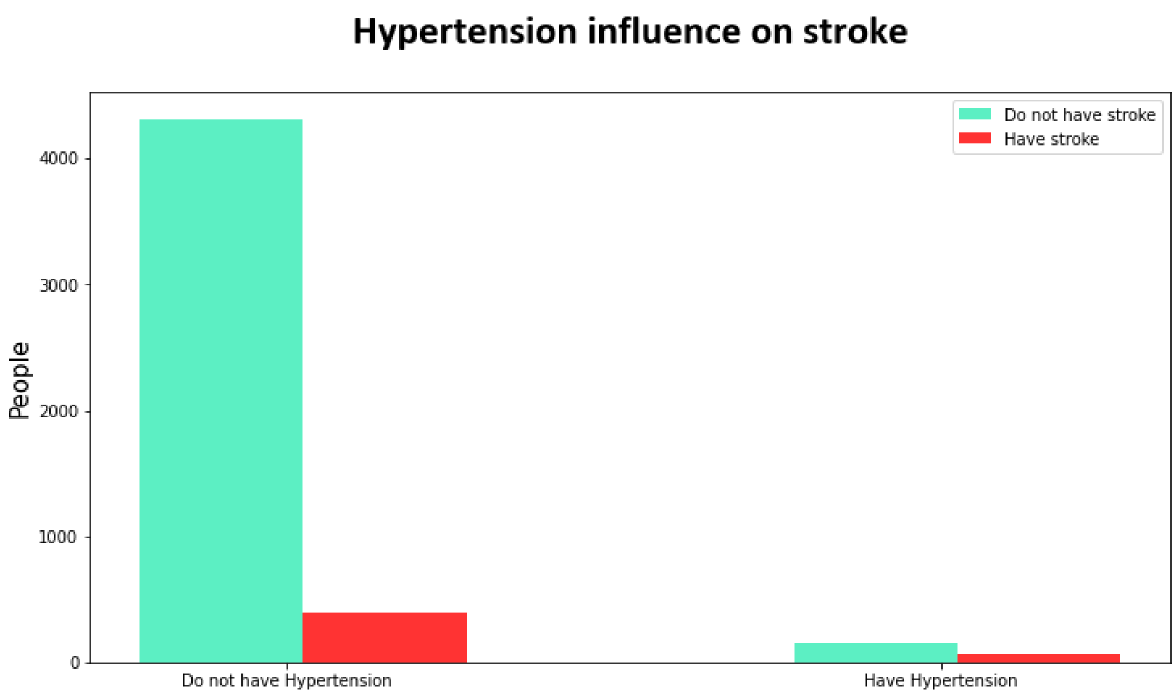
```
HypertensionGroupWithStroke = data.groupby(['hypertension','stroke']).count()['id'][[1
HypertensionGroupWithStroke
```

Out[31]:

```
hypertension  stroke
1             0         391
              1          60
Name: id, dtype: int64
```

In [32]:

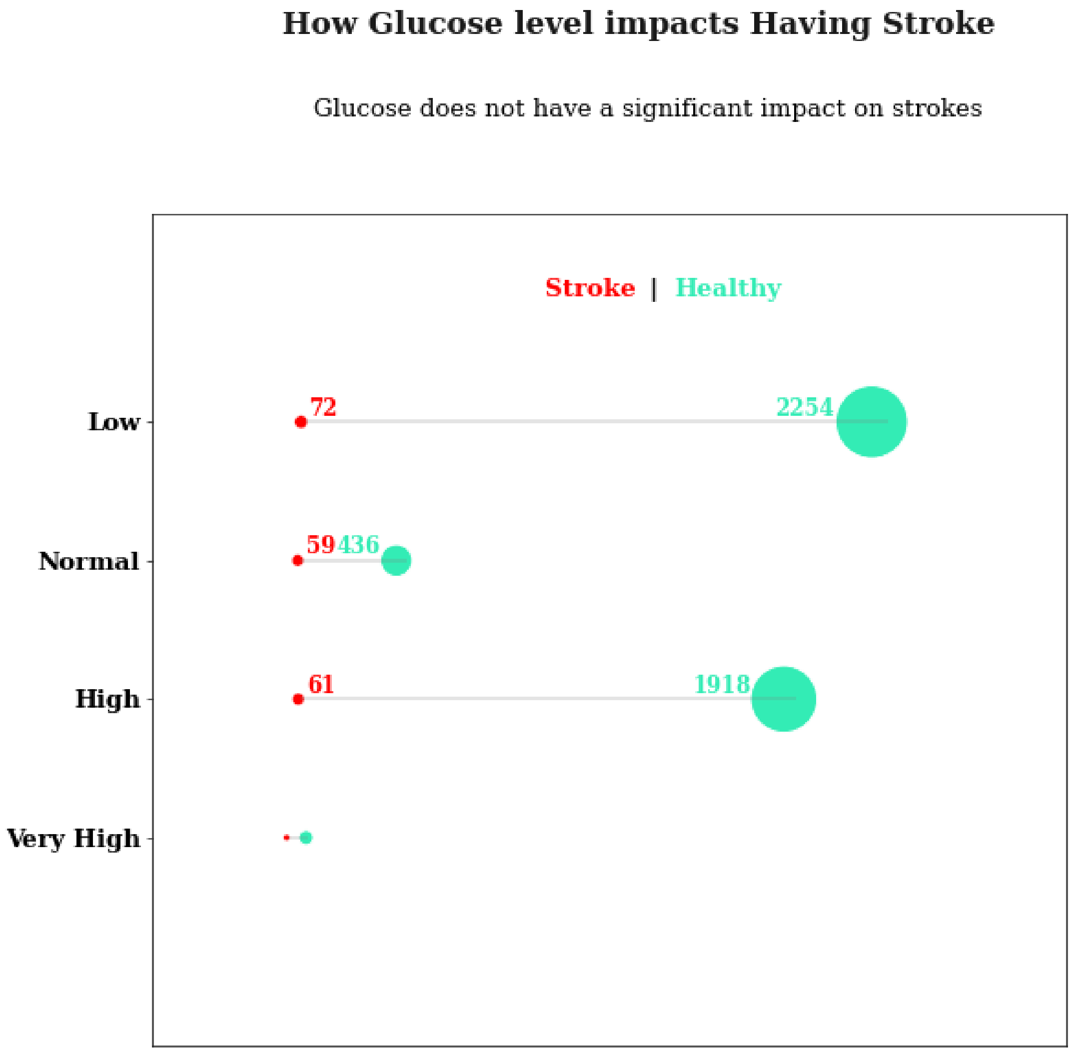
```
n_groups = 2

# create plot
plt.figure(figsize=(12,6.5))
indexx = np.arange(n_groups)
bar_width = 0.25
opacity = 0.8

rects1 = plt.bar(indexx, HypertensionGroupWithoutStroke, bar_width,
alpha=opacity,
color= palette2[0],
label='Do not have stroke')

rects2 = plt.bar(indexx + bar_width, HypertensionGroupWithStroke, bar_width,
alpha=opacity,
color='#ff0000',
label='Have stroke')

plt.xlabel('', size=15)
plt.ylabel('People',size=15)
plt.title('Hypertension influence on stroke\n',size=25, **hfont)
plt.xticks(indexx + 0.1,('Do not have Hypertension', 'Have Hypertension'))
plt.legend()
plt.savefig("Visualizations\HypertensionInfluenceOnStroke.png")
plt.show()
```



From the above diagram, it shows that there is an higher risk for people that have Hypertension to have stroke

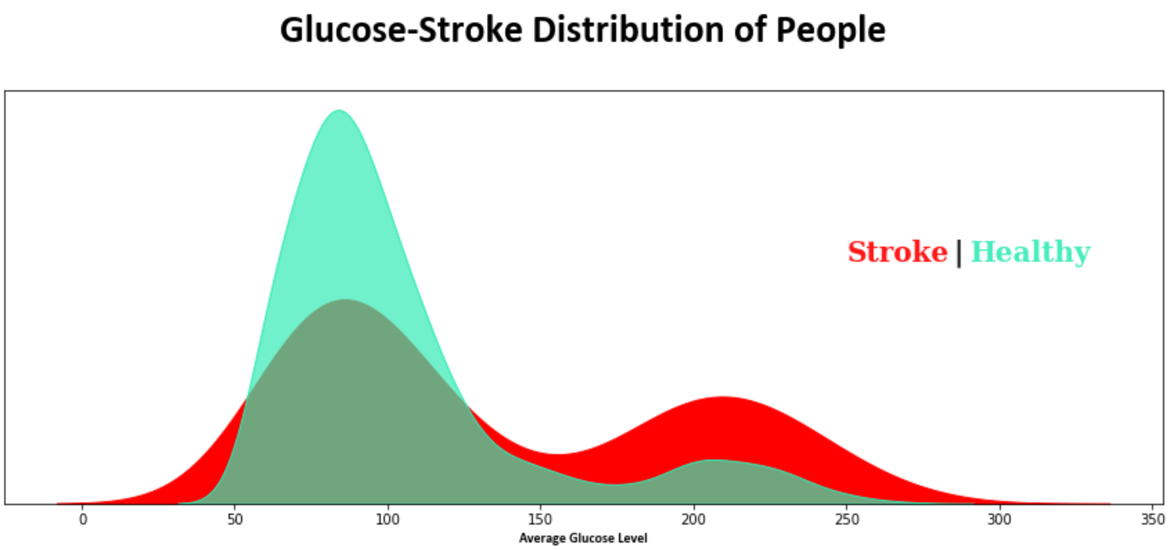
In [33]:

```
# Let's Visualize those that have Stroke using the Glucose Level Category using a dumbe

fig = plt.figure(figsize = (24,10), dpi = 60)

gs = fig.add_gridspec(10,24)
gs.update(wspace = 1, hspace = 0.05)

ax1 = fig.add_subplot(gs[0:,13:]) #dumbbell plot
stroke_glucose = data[data['stroke'] == 1].glucose_cat.value_counts()
healthy_glucose = data[data['stroke'] == 0].glucose_cat.value_counts()

ax1.hlines(y = ['Very High', 'High', 'Normal', 'Low'], xmin = [18,71,71,89],
          xmax = [101,1966,478,2316], color = 'grey',**{'linewidth':0.5})


sns.scatterplot(y = stroke_glucose.index, x = stroke_glucose.values[[0,2,1,3]], s = str
sns.scatterplot(y = healthy_glucose.index, x = healthy_glucose.values[[0,2,1,3]], s = h

ax1.axes.get_xaxis().set_visible(False)
ax1.set_xlim(xmin = -500, xmax = 3000)
ax1.set_ylim(ymin = -1.5,ymax = 4.5)

ax1.set_yticklabels( labels = ['Very High', 'High', 'Normal', 'Low'],fontdict = {'font

ax1.text(0,5.8, 'How Glucose level impacts Having Stroke' ,{'font': 'Serif', 'Size': '
ax1.text(1000,3.9, '\nStroke ', {'font': 'Serif','weight':'bold','Size': '16','weight'
ax1.text(1400,3.9, '\n|', {'color':'black' , 'size':'16', 'weight': 'bold'})
ax1.text(1500,3.9, '\nHealthy', {'font': 'Serif','weight':'bold', 'Size': '16','style'
ax1.text(120,5., 'Glucose does not have a significant impact on strokes\n',
        {'font':'Serif', 'size':'16','color': 'black'})

ax1.text(stroke_glucose.values[0] + 30,3.05, stroke_glucose.values[0], {'font':'Serif'
ax1.text(healthy_glucose.values[0] - 370,3.05, healthy_glucose.values[0], {'font':'Ser

ax1.text(stroke_glucose.values[2] + 30,2.05, stroke_glucose.values[2], {'font':'Serif'
ax1.text(healthy_glucose.values[2] - 230,2.05, healthy_glucose.values[2], {'font':'Ser

ax1.text(stroke_glucose.values[1] + 30,1.05, stroke_glucose.values[1], {'font':'Serif'
ax1.text(healthy_glucose.values[1] - 350,1.05, healthy_glucose.values[1], {'font':'Ser
plt.savefig("Visualizations\GlucoseLevelImpactonStroke.png")
plt.show()
```


How Glucose level impacts Having Stroke
Glucose does not have a significant impact on strokes
Stroke | Healthy
Low
Normal
High
Very High
72
2254
59
436
61
1918

In [34]:

```
fig = plt.figure(figsize=(15, 5.5))
ax = fig.add_subplot(111)
plt.title('Glucose-Stroke Distribution of People\n', size=28, **hfont)
ax.grid(False)
ax.axes.get_yaxis().set_visible(False)
ax.text(250, 0.01, 'Stroke', {'font': 'Serif',
                             'size': '20',
                             'weight': 'bold',
                             'color': '#ff0000'}, alpha=0.9)

ax.text(285, 0.01, '|', {'font': 'Serif',
                       'size': '20',
                       'weight': 'bold',
                       'color': 'black'}, alpha=0.9)

ax.text(290, 0.01, 'Healthy', {'font': 'Serif',
                              'size': '20',
                              'weight': 'bold',
                              'color': palette2[0]}, alpha=0.9)

sns.kdeplot(data=data[data.stroke == 1],
            x='avg_glucose_level', shade=True, ax=ax, color='#ff0000', alpha=1)
sns.kdeplot(data=data[data.stroke == 0],
            x='avg_glucose_level', shade=True, ax=ax, color=palette2[0], alpha=0.7)
plt.xlabel('Average Glucose Level', **hfont)
plt.savefig("Visualizations\GlucoseLevelonStroke.png")
plt.show()
```



In [35]:

```
data[data.stroke == 1]
```

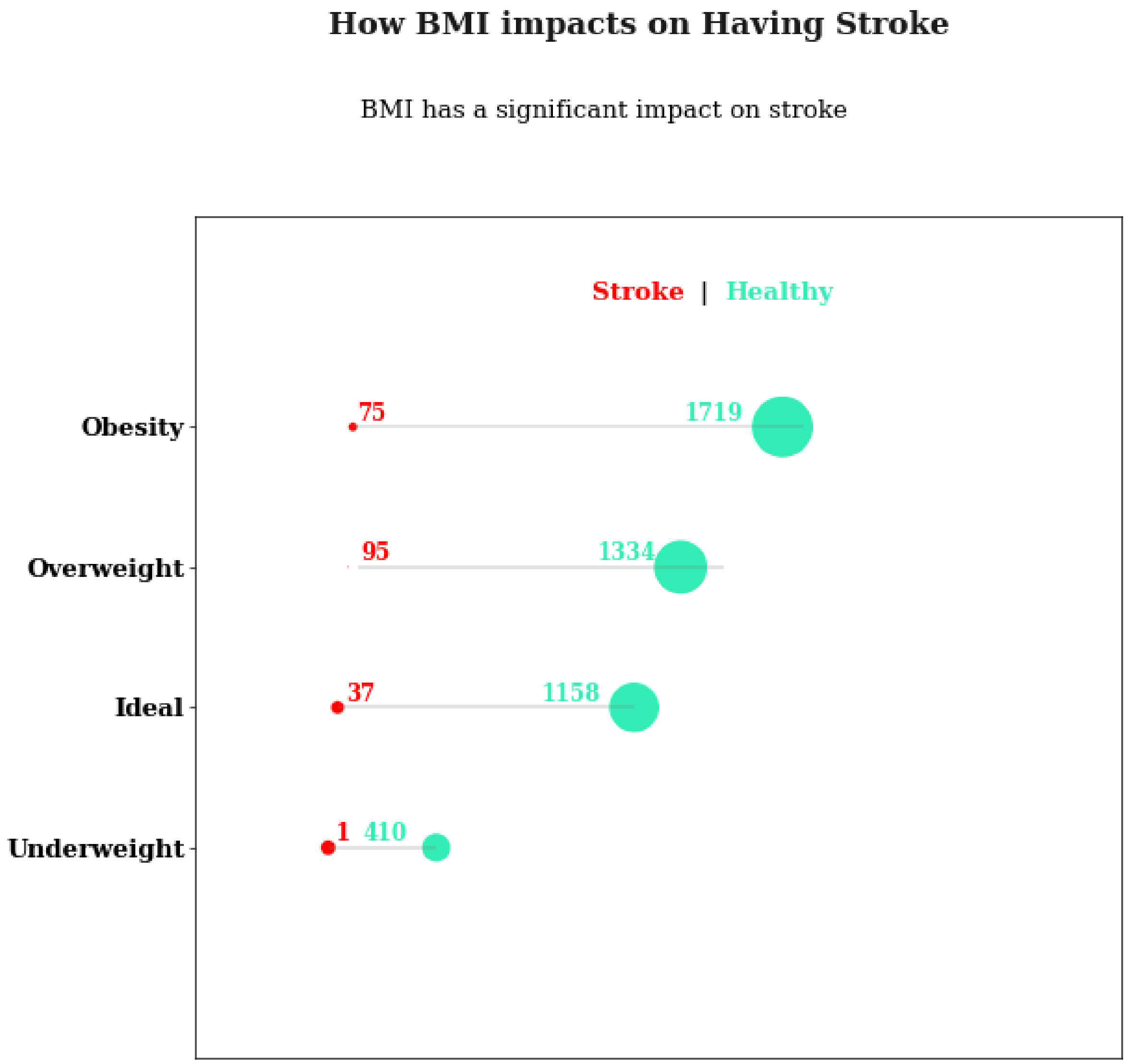
Out[35]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_typ
0	9046	Male	67	0	1	Yes	Private	Urba
2	31112	Male	80	0	1	Yes	Private	Rura
3	60182	Female	49	0	0	Yes	Private	Urba
4	1665	Female	79	1	0	Yes	Self-employed	Rura
5	56669	Male	81	0	0	Yes	Private	Urba
...	...	...	...	...	...	...	...	.
243	40460	Female	68	1	1	Yes	Private	Urba
244	17739	Male	57	0	0	Yes	Private	Rura
245	49669	Female	14	0	0	No	children	Rura
246	27153	Female	75	0	0	Yes	Self-employed	Rura
248	43424	Female	78	0	0	Yes	Private	Rura

209 rows × 15 columns

In [36]:

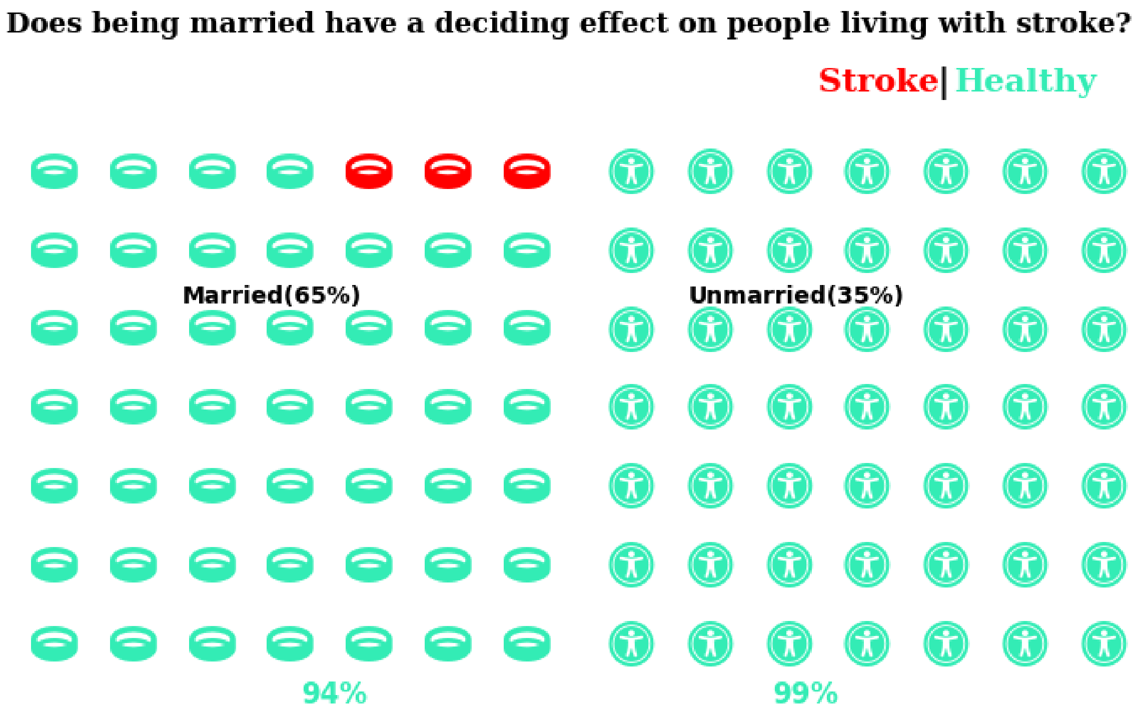
```
# Let's Visualize those that have Stroke using the BMI Levels Category using a dumbell

fig = plt.figure(figsize = (24,10), dpi = 60)

gs = fig.add_gridspec(10,24)
gs.update(wspace = 1, hspace = 0.05)

ax1 = fig.add_subplot(gs[0:,13:]) #dumbbell plot
stroke_bmi = data[data['stroke'] == 1].bmi_cat.value_counts()
healthy_bmi = data[data['stroke'] == 0].bmi_cat.value_counts()

ax1.hlines(y = ['Underweight','Ideal','Overweight','Obesity'], xmin = [1,37,115,96],
          xmax = [410,1158,1495,1797], color = 'grey',**{'linewidth':0.5})


sns.scatterplot(y = stroke_bmi.index[[3,2,0,1]], x = stroke_bmi.values[[3,2,0,1]], s =
sns.scatterplot(y = healthy_bmi.index[[0,1,2,3]], x = healthy_bmi.values[[0,1,2,3]], s

ax1.axes.get_xaxis().set_visible(False)
ax1.set_xlim(xmin = -500, xmax = 3000)
ax1.set_ylim(ymin = -1.5,ymax = 4.5)

ax1.set_yticklabels( labels = ['Underweight','Ideal','Overweight','Obesity'],fontdict =

ax1.text(0,5.8, 'How BMI impacts on Having Stroke' ,{'font': 'Serif', 'Size': '20','we
ax1.text(1000,3.9, '\nStroke ', {'font': 'Serif','weight':'bold','Size': '16','weight'
ax1.text(1400,3.9, '\n|', {'color':'black' , 'size':'16', 'weight': 'bold'})
ax1.text(1500,3.9, '\nHealthy', {'font': 'Serif','weight':'bold', 'Size': '16','style'
ax1.text(120,5., 'BMI has a significant impact on stroke\n',
        {'font':'Serif', 'size':'16','color': 'black'})

ax1.text(stroke_bmi.values[1] + 30,3.05, stroke_bmi.values[1], {'font':'Serif', 'Size'
ax1.text(healthy_bmi.values[0] - 370,3.05, healthy_bmi.values[0], {'font':'Serif', 'Si

ax1.text(stroke_bmi.values[0] + 30,2.05, stroke_bmi.values[0], {'font':'Serif', 'Size'
ax1.text(healthy_bmi.values[1] - 320,2.05, healthy_bmi.values[1], {'font':'Serif', 'Si

ax1.text(stroke_bmi.values[2] + 30,1.05, stroke_bmi.values[2], {'font':'Serif', 'Size'
ax1.text(healthy_bmi.values[2] - 350,1.05, healthy_bmi.values[2], {'font':'Serif', 'Si

ax1.text(stroke_bmi.values[3] + 30,0.05, stroke_bmi.values[3], {'font':'Serif', 'Size'
ax1.text(healthy_bmi.values[3] - 280,0.05, healthy_bmi.values[3], {'font':'Serif', 'Si
plt.savefig("Visualizations\BMILevelOnStroke.png")
plt.show()

```


How BMI impacts on Having Stroke
BMI has a significant impact on stroke
Stroke | Healthy
Obesity
75
1719
Overweight
95
1334
Ideal
37
1158
Underweight
1
410

In [37]:

```
stroke_married = data[data['stroke'] == 1]['ever_married'].value_counts()
healthy_married = data[data['stroke'] == 0]['ever_married'].value_counts()

yes = data['ever_married'].value_counts().values[0]
no =  data['ever_married'].value_counts().values[1]

stroke_no = int(round (stroke_married.values[1] / no * 100, 0))
stroke_yes = int(round( stroke_married.values[0] / yes *100, 0))
healthy_no = int(round(healthy_married.values[1] / no * 100, 0))
healthy_yes = int(round(healthy_married.values[0] / yes *100, 0))

no_per = int(round(no/(no+yes) * 100, 0))
yes_per = int(round(yes/(no+yes)* 100, 0))


fig = plt.figure(FigureClass = Waffle,
                 constrained_layout = True,
                 figsize = (7,7),
                 facecolor = '#fff',dpi = 100,

                 plots = {'121':
                          {
                           'rows':7,
                           'columns': 7,
                           'values' : [stroke_yes,healthy_yes],
                            'colors' : ['#ff0000',palette2[0]],
                              'vertical' : True,
                              'interval_ratio_x': 0.005,
                              'interval_ratio_y': 0.005,
                              'icons' : 'ring',
                              'icon_legend': False,
                              'icon_size':20,
                              'plot_anchor':'C',
                              'alpha':0.8,
                              'starting_location': 'NE'
                          },

                          '122' :
                          {
                            'rows': 7,
                            'columns':7,
                            'values':[stroke_no,healthy_no],
                              'colors' : ['#ff0000',palette2[0]],
                              'vertical': True,
                              'interval_ratio_x': 0.005,
                              'interval_ratio_y':0.005,
                              'icons' : 'universal-access',
                              'icon_legend' :False,
                              'icon_size':20,
                              'plot_anchor':'C',
                              'alpha':0.8,
                              'starting_location': 'NE'

                           }
                         },

)
fig.text(0., 0.8, 'Does being married have a deciding effect on people living with stro
fig.text(0.25, 0.23, '{}%'.format(healthy_yes), {'size':12,'weight':'bold' , 'color':pa
```

```
fig.text(0.65, 0.23, '{}%'.format(healthy_no), {'size':12,'weight':'bold', 'color':pal
fig.text(0.15, 0.57, 'Married({}%)'.format(yes_per), {'size':10,'weight':'bold' ,'colo
fig.text(0.58, 0.57, "Unmarried({}%)".format(no_per), {'size':10,'weight':'bold', 'col
fig.text(0.69,0.75, 'Stroke ', {'font': 'Serif','weight':'bold','Size': '14','weight':
fig.text(0.79,0.75, '|', {'color':'black' , 'size':'14', 'weight': 'bold'})
fig.text(0.805,0.75, 'Healthy', {'font': 'Serif','weight':'bold', 'Size': '14','style'
plt.savefig("Visualizations\MarriageDistribution.png")
fig.show()
```



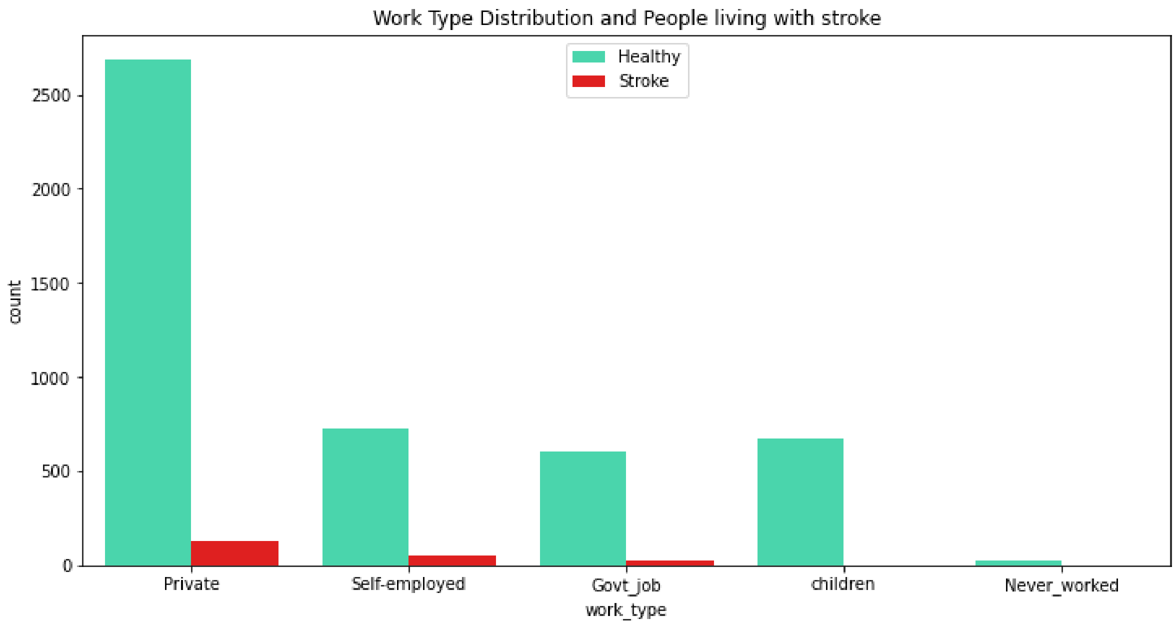
Risk of stroke in married people is relatively high

In [38]:

```
# Work Type
```

In [39]:

```
# using countplot to plot for Work Type
plt.figure(figsize = (12,6))
labels=['Healthy','Stroke']
s = sns.countplot(x="work_type", hue="stroke", data=data,palette=palette2)
h,l = s.get_legend_handles_labels()
s.legend(h,labels, title="")
plt.title("Work Type Distribution and People living with stroke",size=12)
plt.savefig("Visualizations\WorkTypeDistribution.png")
plt.show()
```

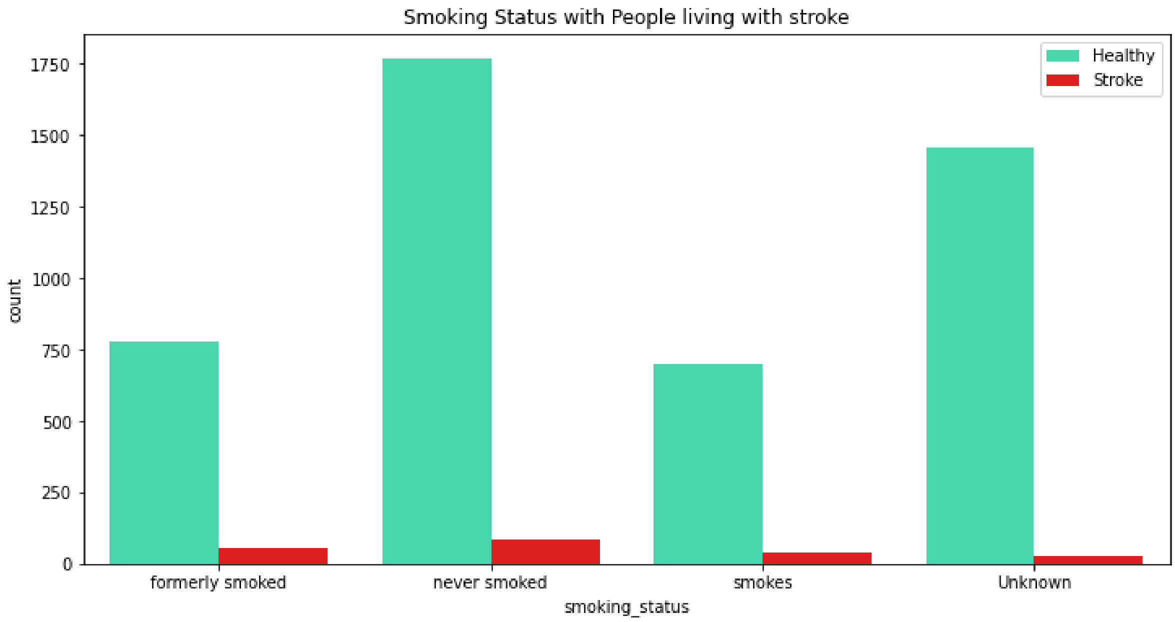


In [40]:

```
# Smoking
```

In [41]:

```
# using countplot to plot for Work Type
plt.figure(figsize = (12,6))
labels=['Healthy','Stroke']
s = sns.countplot(x="smoking_status", hue="stroke", data=data,palette=palette2)
h,l = s.get_legend_handles_labels()
s.legend(h,labels, title="")
plt.title("Smoking Status with People living with stroke",size=12)
plt.savefig("Visualizations\SmokingStatus.png")
plt.show()
```



Modelling and Results

In [44]:

```
data = data.drop(['bmi_cat','age_cat','glucose_cat'],axis='columns')
data = pd.get_dummies(data,drop_first=True)
data.head()
```

Out[44]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	stroke	gender_Male	evei
0	9046	67	0	1	228.69	36.6	1	1	
2	31112	80	0	1	105.92	32.5	1	1	
3	60182	49	0	0	171.23	34.4	1	0	
4	1665	79	1	0	174.12	24.0	1	0	
5	56669	81	0	0	186.21	29.0	1	1	

In [45]:

```
X = data.drop(['stroke','id'],axis='columns')
X.head()
```

Out[45]:

	age	hypertension	heart_disease	avg_glucose_level	bmi	gender_Male	ever_married_Yes
0	67	0	1	228.69	36.6	1	1
2	80	0	1	105.92	32.5	1	1
3	49	0	0	171.23	34.4	0	1
4	79	1	0	174.12	24.0	0	1
5	81	0	0	186.21	29.0	1	1

In [46]:

```
y = data.stroke
```

In [47]:

```
X.shape,y.shape
```

Out[47]:

```
((4908, 15), (4908,))
```

In [48]:

```
X.head()
```

Out[48]:

	age	hypertension	heart_disease	avg_glucose_level	bmi	gender_Male	ever_married_Yes
0	67	0	1	228.69	36.6	1	1
2	80	0	1	105.92	32.5	1	1
3	49	0	0	171.23	34.4	0	1
4	79	1	0	174.12	24.0	0	1
5	81	0	0	186.21	29.0	1	1

In [49]:

```
y[:5]
```

Out[49]:

```
0    1
2    1
3    1
4    1
5    1
Name: stroke, dtype: int64
```

HYPERPARAMETER TUNING

In [46]:

```
#Python Dictionary with 5 supervised models and parameters to choose the best Models ar

model_params = {
    'Decision Tree': {
        'model' : DecisionTreeClassifier(),
        'params' : {
            'criterion':['gini','entropy'],
            'splitter': ['best','random'],
            'max_depth': [10,20,30,100],
            'random_state': [1,2,10]
        }
    },
    'Random_forest':{
        'model' : RandomForestClassifier(),
        'params' : {
            'n_estimators': [1,5,100],
            'n_jobs': [1,10,20],
            'random_state': [1,2,10]
        }
    },
    'Logistic_regression' :{
        'model' : LogisticRegression(),
        'params': {
            'C': [1,5,10],
            'solver':['liblinear','saga'],
            'multi_class':['auto'],
            'random_state': [1,2,10],
            'penalty': ['l1','l2','elasticnet','none']
        }
    },
    'K_Nearest_Neighbour' :{
        'model' : KNeighborsClassifier(),
        'params' :{
            'n_neighbors': [1,5,10],
            'algorithm': ["auto", "brute", "kd_tree", "ball_tree"],
            'weights': ['uniform','distance'],
            'n_jobs' : [1,10,20]
        }
    },
    'Gradient_Boost': {
        'model': GradientBoostingClassifier(),
        'params' :{
            'learning_rate': [0.01],
            'loss': ['exponential'],
            'max_depth': [50,70],
            'max_features': [1,2],
            'n_estimators': [200,300]
        }
    }
}
```

In [47]:

```
scores = [] #check list comprehension

for model_name,mp in model_params.items():
    X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,random_state=1,:
    sm = SMOTE(random_state=0)
    X_train,y_train = sm.fit_resample(X_train,y_train)
    scaler = StandardScaler()
    X_train = scaler.fit_transform(X_train)
    rs = GridSearchCV(mp['model'],mp['params'],cv=5,return_train_score=False)
    rs.fit(X_train,y_train)
    scores.append({
        'Model': model_name,
        'Best_Score': rs.best_score_,
        'Best_Parameters':rs.best_params_
    })
```

In [48]:

```
pd.options.display.max_colwidth = 200
scoresdf = pd.DataFrame(scores,columns=['Model','Best_Score','Best_Parameters'])
scoresdf.sort_values(by='Best_Score',ascending=False, inplace=True)
scoresdf
```

Out[48]:

	Model	Best_Score	Best_Parameters
4	Gradient_Boost	0.956374	{'learning_rate': 0.01, 'loss': 'exponential', 'max_depth': 70, 'max_features': 2, 'n_estimators': 300}
1	Random_forest	0.952251	{'n_estimators': 100, 'n_jobs': 1, 'random_state': 10}
3	K_Nearest_Neighbour	0.929505	{'algorithm': 'auto', 'n_jobs': 1, 'n_neighbors': 1, 'weights': 'uniform'}
0	Decision Tree	0.927110	{'criterion': 'gini', 'max_depth': 30, 'random_state': 2, 'splitter': 'random'}
2	Logistic_regression	0.858744	{'C': 1, 'multi_class': 'auto', 'penalty': 'l2', 'random_state': 1, 'solver': 'liblinear'}

In [49]:

```
# The above table shows the Model and Parameters with the best score in a descending o
# So we use the Models and the Parameters displayed in our table above for all our alg
```

In [50]:

```
# Function that accepts (X,y,model_name,model,random_state,Datasplit and parameters pe
# the model score and stores it in model_results.
```

In [50]:

```
models_results = {}

def show_model_results(X,y,model_name,model,rand_state,Datasplit=0.2,**kwargs):
    print(f'The model {model_name} with parameters : {kwargs}')
    # Create an object m of the model with parameters entered into the function
    m = model(**kwargs)
    # Split data into training and testing set
    X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=Datasplit,random_st
    # Create an object of a SMOTE (Oversampling library)
    sm = SMOTE(random_state=0)
    # Performing oversampling on our train set
    X_train,y_train = sm.fit_resample(X_train,y_train)
    # Create an object of our scaling class
    scaler = StandardScaler()
    # Scale our X set
    X_train = scaler.fit_transform(X_train)
    X_test = scaler.transform(X_test)
    # Model training
    m.fit(X_train,y_train)
    # Get model score
    score = m.score(X_test,y_test)
    # Get model predictions
    prediction = m.predict(X_test)
    # Get model precision score
    model_precision = precision_score(y_test,prediction)
    # Get model recall score
    recall = recall_score(y_test,prediction)
    # Get model F1 score
    F1 = f1_score(y_test,prediction)
    print('')
    print('****************************************************************')
    print(f'Model name:        \t {model_name}')
    print(f'Model Parameters:  \t {kwargs}')
    print(f'Model Score:       \t {score*100}')
    print(f'Model Precision Score:   {model_precision*100}')
    print(f'Model Recall Score:  \t {recall*100}')
    print(f'Model F1 Score:  \t {F1*100}')
    print('****************************************************************')
    # Call function plot_confusion matrix
    plot_confusion_matrics(m,X_test,y_test,model_name)
    return score,model_name,F1,model_precision,recall
# Function to plot our models confusion matrix
def plot_confusion_matrics(model, X_test, y_test,model_name):
    # Get model prediction
    y_pred = model.predict(X_test)
    # confusion matrix
    matrix = confusion_matrix(y_test, y_pred)
    # Dataframe to store values
    df_cm = pd.DataFrame(matrix, index = ['Stroke', 'Healthy'],
                             columns = ['Stroke', 'Healthy'])
    plt.figure(figsize = (12,8))
    #plot confusion matrix
    sns.heatmap(df_cm,
                annot=True,
                cmap='Greens',
                fmt='.5g',
                annot_kws={"size": 20}).set_title('Confusion matrix', fontsize = 35, y
    plt.xlabel('Predicted values', fontsize = 20, **hfont)
```

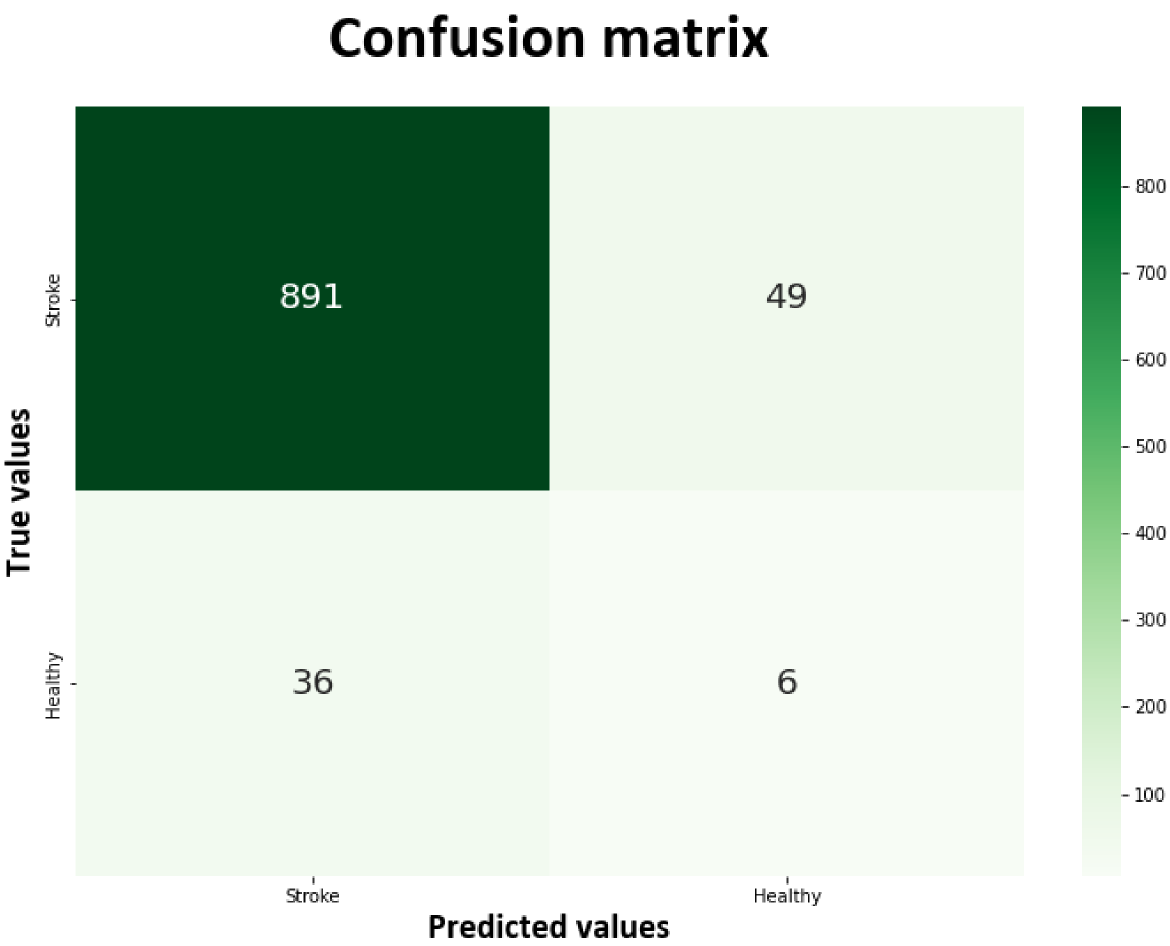
```
    plt.ylabel('True values', fontsize = 20, **hfont)
    plt.savefig(f"Visualizations\{model_name}.png")
    plt.show()
```

1. RANDOM FOREST CLASSIFIER

In [51]:

```
rnd_state = 2
# Call show model result and pass parameters from Hyperparameter tuning
output = show_model_results(X,y,'Random Forest',RandomForestClassifier,n_estimators=10
# Save outputs in a dictionary
models_resultsRC = ({
    'Model Name': output[1],
    'Model Score': output[0],
    'F1 Score': output[2],
    'Precision Score': output[3],
    'Recall Score': output[4]
})
```

```
The model Random Forest with parameters : {'n_estimators': 100, 'n_jobs': 1}

***************************************************************
Model name:               Random Forest
Model Parameters:         {'n_estimators': 100, 'n_jobs': 1}
Model Score:              91.34419551934828
Model Precision Score:    10.909090909090908
Model Recall Score:       14.285714285714285
Model F1 Score:           12.371134020618557
***************************************************************
```

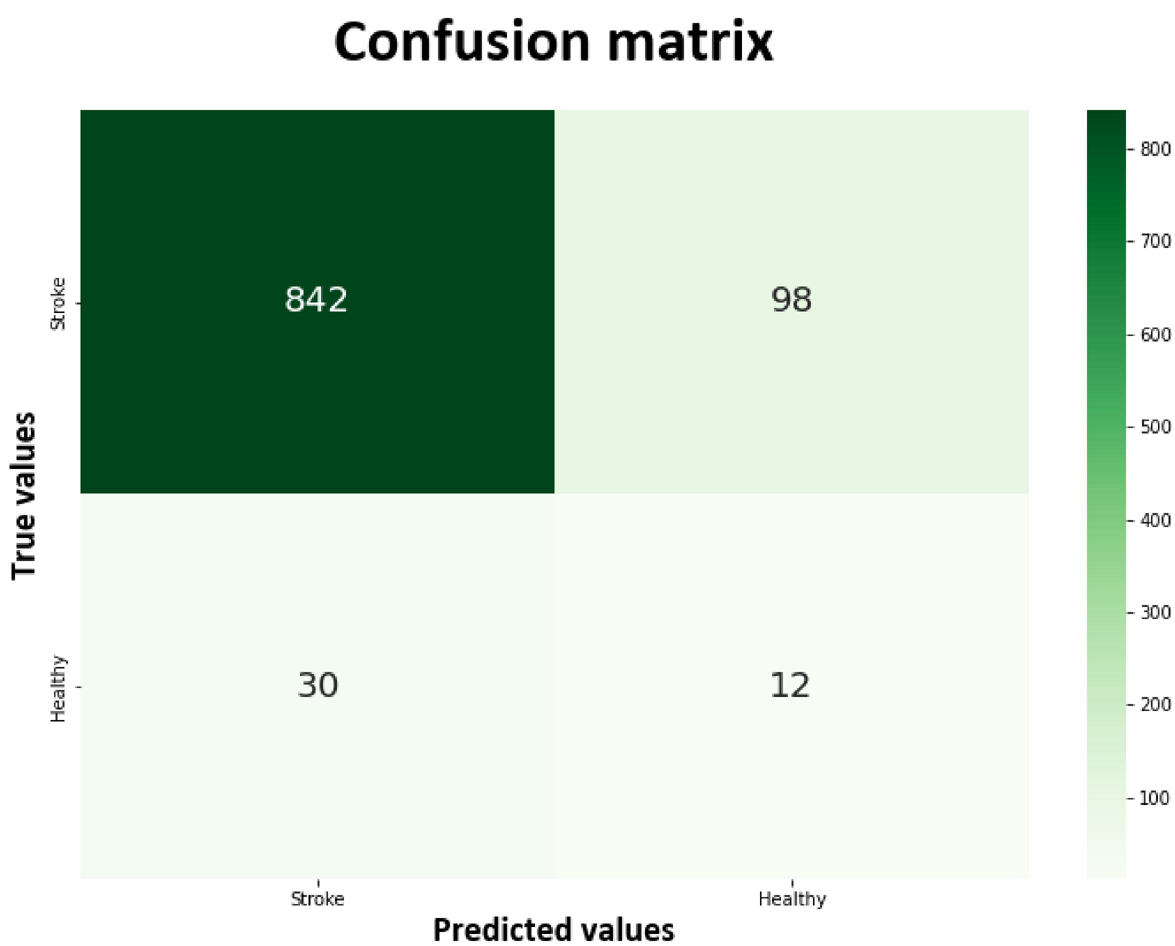


2. K NEAREST NEIGHBOURS

In [52]:

```
rnd_state = 1
# Call show model result and pass parameters from Hyperparameter tuning
output = show_model_results(X,y,'KNN',KNeighborsClassifier,algorithm='auto',n_jobs=1,n_
# Save outputs in a dictionary
models_resultsKN = ({
    'Model Name': output[1],
    'Model Score': output[0],
    'F1 Score': output[2],
    'Precision Score': output[3],
    'Recall Score': output[4]
})
```

```
The model KNN with parameters : {'algorithm': 'auto', 'n_jobs': 1, 'n_neighb
ors': 1, 'weights': 'uniform'}

***************************************************************
Model name:               KNN
Model Parameters:         {'algorithm': 'auto', 'n_jobs': 1, 'n_neighbors':
1, 'weights': 'uniform'}
Model Score:              86.9653767820774
Model Precision Score:    10.909090909090908
Model Recall Score:       28.57142857142857
Model F1 Score:           15.789473684210526
***************************************************************
```

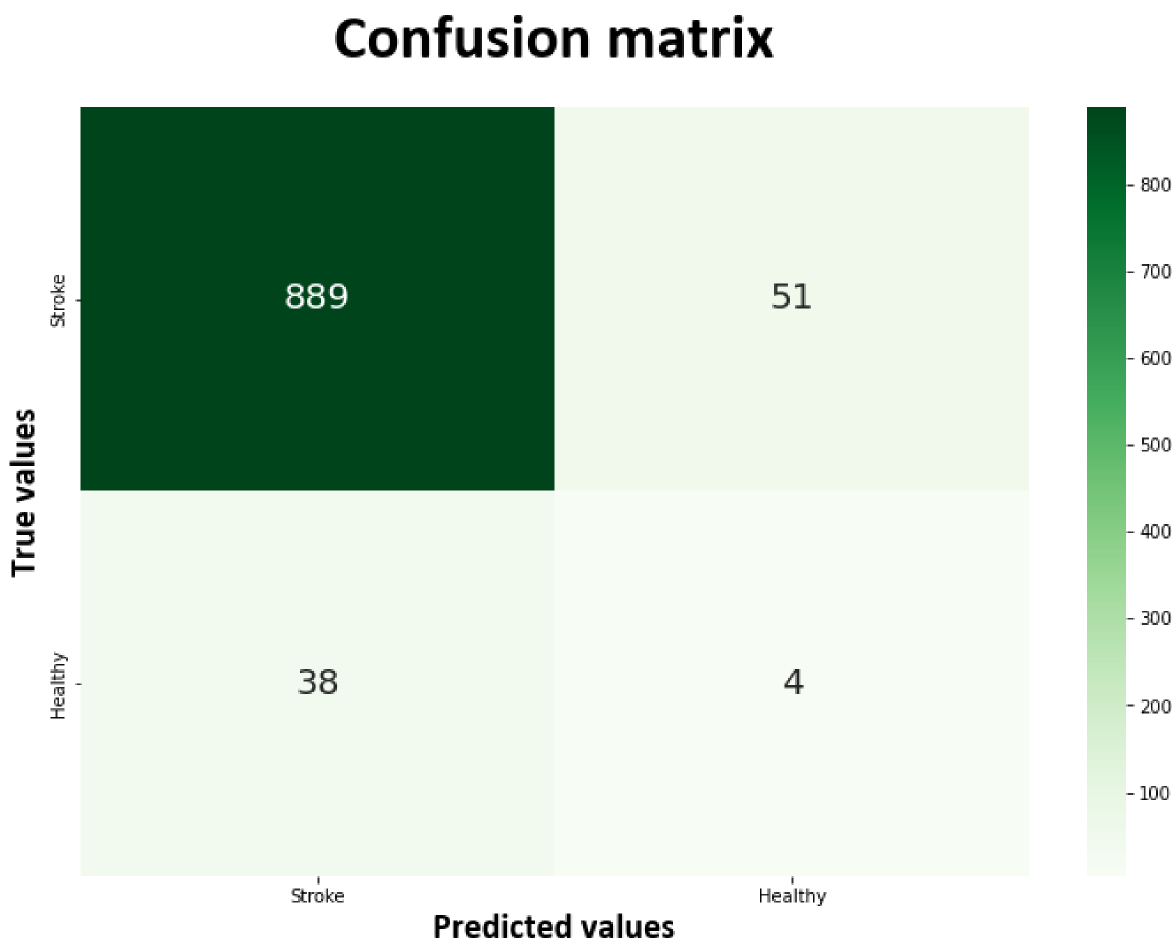


3. Gradient Boost

In [53]:

```
rand_state = 0
# Call show model result and pass parameters from Hyperparameter tuning
output = show_model_results(X, y,'Gradient Boost',GradientBoostingClassifier,learning_r
# Save outputs in a dictionary
models_resultsGB = ({
    'Model Name': output[1],
    'Model Score': output[0],
    'F1 Score': output[2],
    'Precision Score': output[3],
    'Recall Score': output[4]
})
```

```
The model Gradient Boost with parameters : {'learning_rate': 0.01, 'loss':
'exponential', 'max_depth': 70, 'max_features': 1, 'n_estimators': 200}

***************************************************************
Model name:               Gradient Boost
Model Parameters:         {'learning_rate': 0.01, 'loss': 'exponential', 'max
_depth': 70, 'max_features': 1, 'n_estimators': 200}
Model Score:              90.93686354378818
Model Precision Score:    7.2727272727272725
Model Recall Score:       9.523809523809524
Model F1 Score:           8.24742268041237
***************************************************************
```

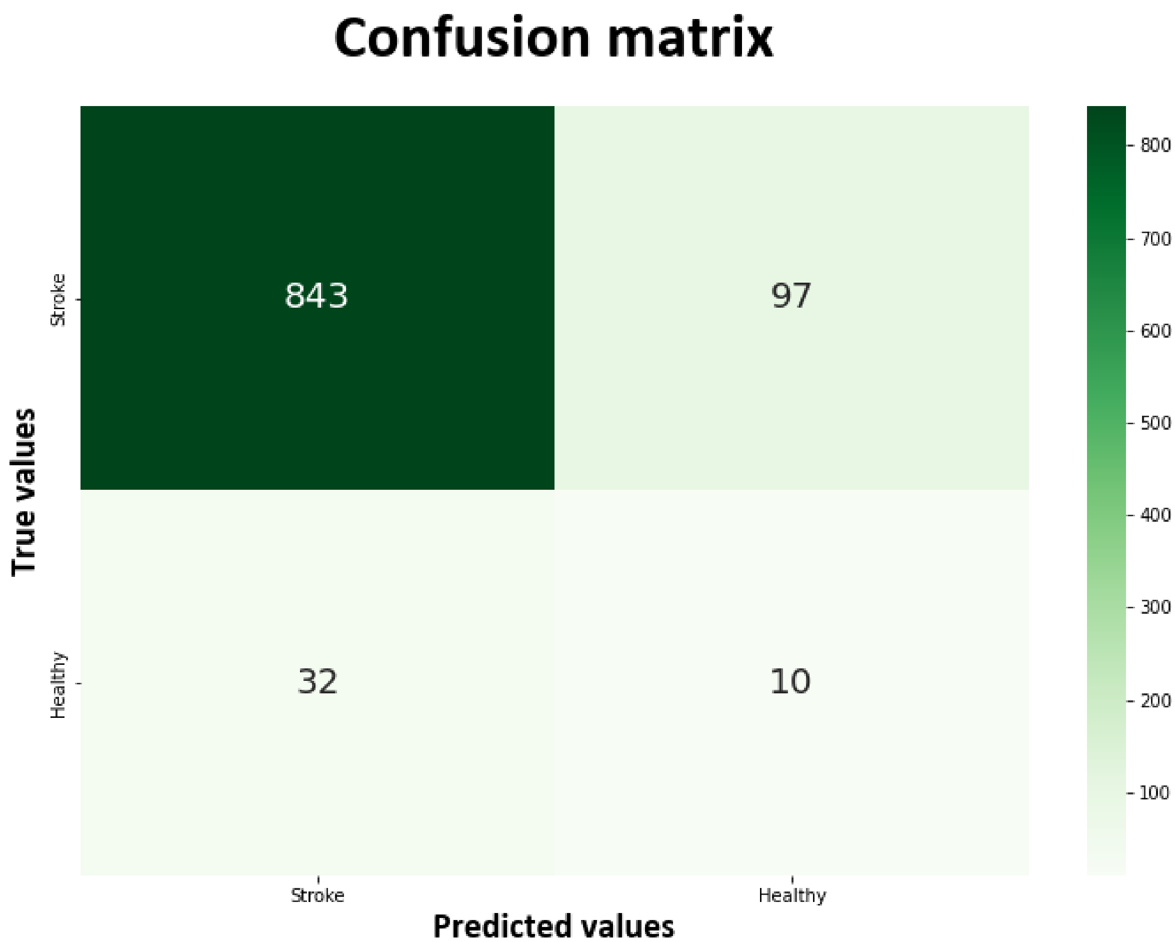


4. Decision Tree

In [54]:

```
# Call show model result and pass parameters from Hyperparameter tuning
output = show_model_results(X,y,'Decision Tree',DecisionTreeClassifier,10,criterion='e
# Save outputs in a dictionary
models_resultsDT = ({
    'Model Name': output[1],
    'Model Score': output[0],
    'F1 Score': output[2],
    'Precision Score': output[3],
    'Recall Score': output[4]
})
```

```
The model Decision Tree with parameters : {'criterion': 'entropy', 'max_dept
h': 20, 'random_state': 2, 'splitter': 'random'}

***************************************************************
Model name:               Decision Tree
Model Parameters:         {'criterion': 'entropy', 'max_depth': 20, 'random_s
tate': 2, 'splitter': 'random'}
Model Score:              86.86354378818737
Model Precision Score:    9.345794392523365
Model Recall Score:       23.809523809523807
Model F1 Score:           13.422818791946309
***************************************************************
```

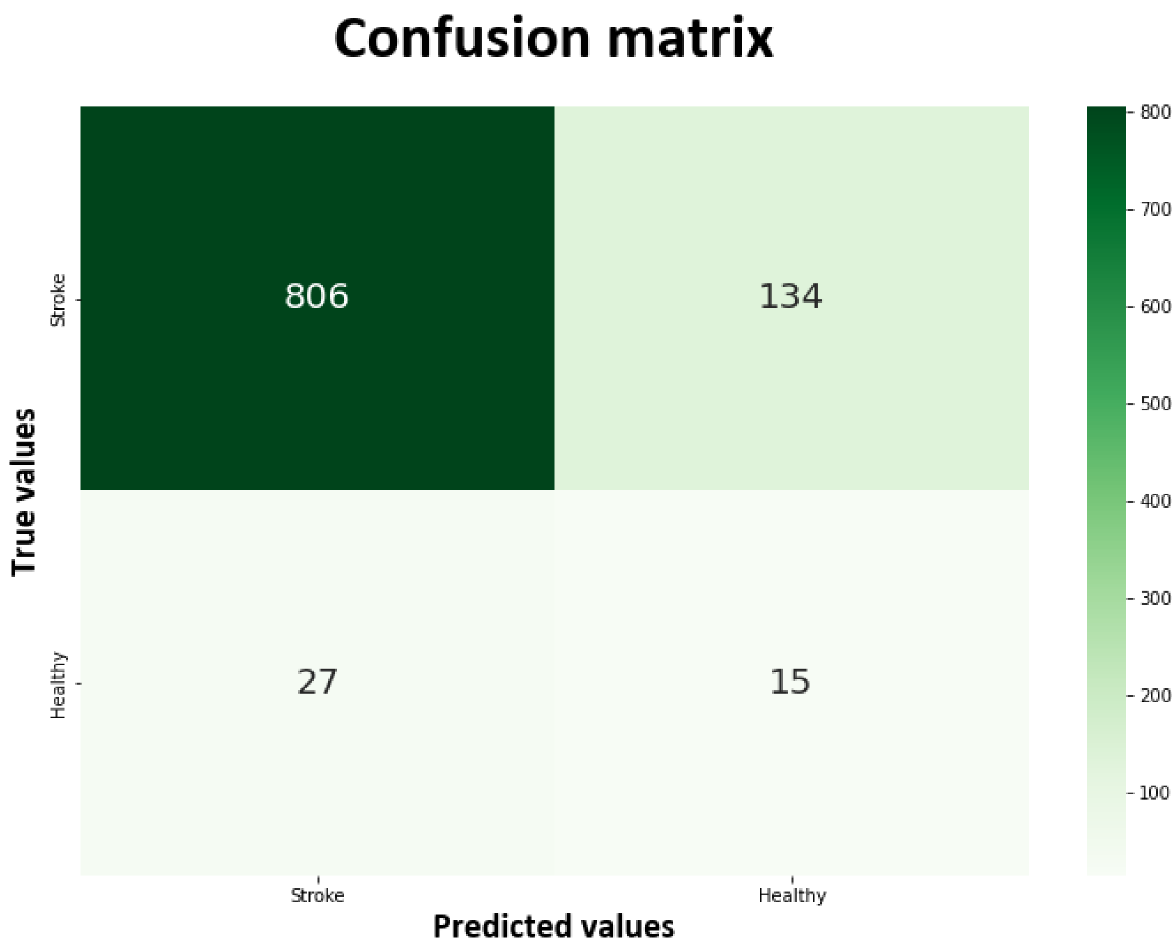


5. Logistic Regression

In [55]:

```
# Call show model result and pass parameters from Hyperparameter tuning
output = show_model_results(X,y,'Logistic Regression',LogisticRegression,2,C=1,multi_c
# Save outputs in a dictionary
models_resultsLR = ({
    'Model Name': output[1],
    'Model Score': output[0],
    'F1 Score': output[2],
    'Precision Score': output[3],
    'Recall Score': output[4]
})
```

```
The model Logistic Regression with parameters : {'C': 1, 'multi_class': 'aut
o', 'penalty': 'none', 'solver': 'saga'}

***************************************************************
Model name:                 Logistic Regression
Model Parameters:           {'C': 1, 'multi_class': 'auto', 'penalty': 'none',
'solver': 'saga'}
Model Score:                83.60488798370672
Model Precision Score:      10.06711409395973
Model Recall Score:         35.714285714285715
Model F1 Score:             15.706806282722512
***************************************************************
```



6. Artificial Neural Network

In [168]:

```
sm = SMOTE(random_state=0)

X_train, X_test, y_train, y_test = train_test_split(X, y,test_size=0.2,random_state=2,s
X_train, y_train = sm.fit_resample(X_train, y_train)
y_train = keras.utils.to_categorical(y_train, 2)
y_test = keras.utils.to_categorical(y_test, 2)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
# Creating a Neural Network with 1 input layer and 3 hidden layers with activation func
# Then one output layer with ***sigmoid*** function
model = keras.Sequential([
    keras.layers.Flatten(input_dim=X_train.shape[1]),
    keras.layers.Dense(500, activation='relu'),
    keras.layers.Dense(250, activation='relu'),
    keras.layers.Dense(125, activation='relu'),
    keras.layers.Dense(2, activation='sigmoid')
])
#Compile our model using Optimizer adam and loss function ,
model.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])
# Model trains for 150 epochs and validates our model on X_test and y_test.
history = model.fit(X_train, y_train, epochs=150,validation_data=(X_test, y_test),verbo
```

In [169]:

```
y_predicted = model.predict(X_test)
y_predicted
```

Out[169]:

```
array([[9.99879479e-01, 5.42283058e-04],
       [1.00000000e+00, 2.25540669e-10],
       [5.42799234e-02, 4.18436527e-01],
       ...,
       [9.96947706e-01, 5.72471619e-02],
       [1.00000000e+00, 1.26689295e-17],
       [1.00000000e+00, 3.40698151e-29]], dtype=float32)
```

In [170]:

```
y_predicted_labels = [np.argmax(i) for i in y_predicted]
y_predicted_labels[:5]
```

Out[170]:

```
[0, 0, 1, 0, 0]
```

In [171]:

```
y_test_labels = [np.argmax(i) for i in y_test]
y_test_labels[:5]
```

Out[171]:

```
[0, 0, 0, 0, 0]
```

In [173]:

```
from sklearn.metrics import classification_report
# Print-Out our classification Report
print(classification_report(y_test_labels,y_predicted_labels))
```

```
              precision    recall  f1-score   support

           0       0.96      0.93      0.95       940
           1       0.10      0.17      0.12        42

    accuracy                           0.90       982
   macro avg       0.53      0.55      0.54       982
weighted avg       0.92      0.90      0.91       982
```

In [174]:

```
from sklearn.metrics import f1_score, precision_score, recall_score, confusion_matrix
# Print f1, precision, and recall scores
preScore = precision_score(y_test_labels,y_predicted_labels, average="macro")
recScore = recall_score(y_test_labels,y_predicted_labels, average="macro")
f1Score = f1_score(y_test_labels,y_predicted_labels, average="macro")
print(f"Precision Score = {preScore}")
print(f"Recall Score = {recScore}")
print(f"F1 Score = {f1Score}")
```

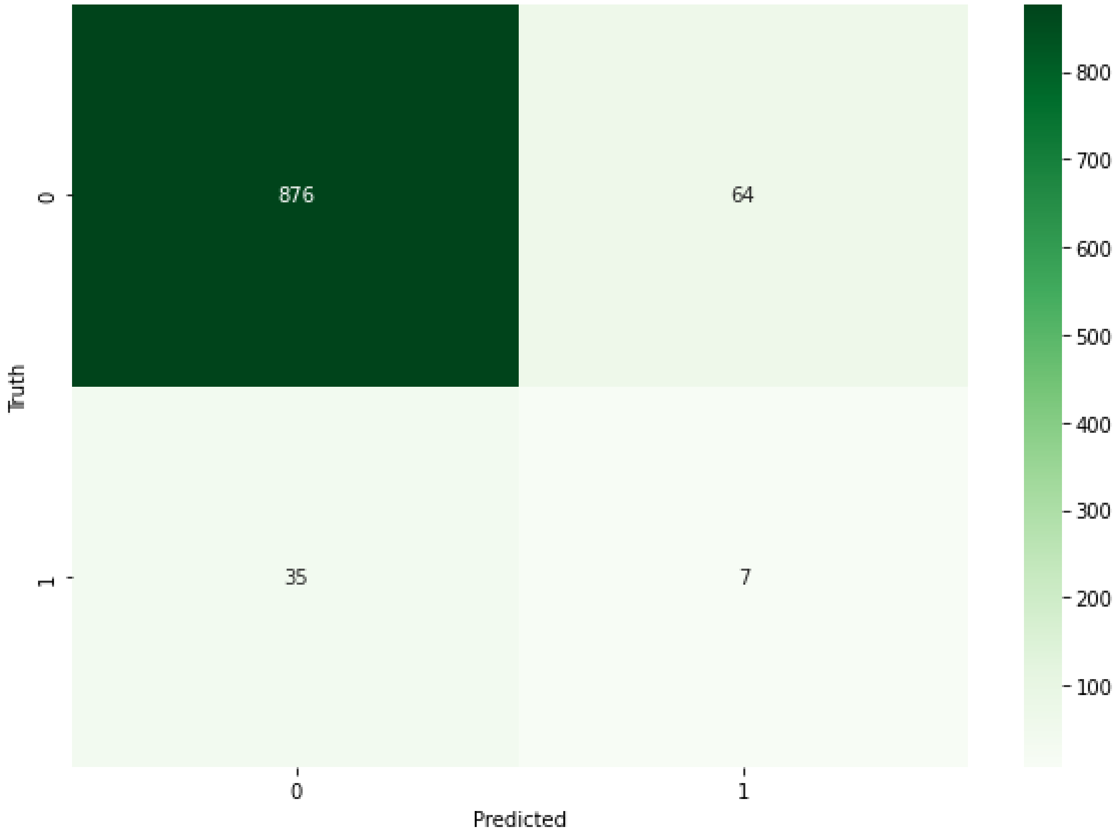
```
Precision Score = 0.530086114933288
Recall Score = 0.549290780141844
F1 Score = 0.5352046011961963
```

In [175]:

```
cm = tf.math.confusion_matrix(labels=y_test_labels,predictions=y_predicted_labels)
plt.figure(figsize=(10,7))
sns.heatmap(cm,annot=True,fmt='d',cmap='Greens')
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

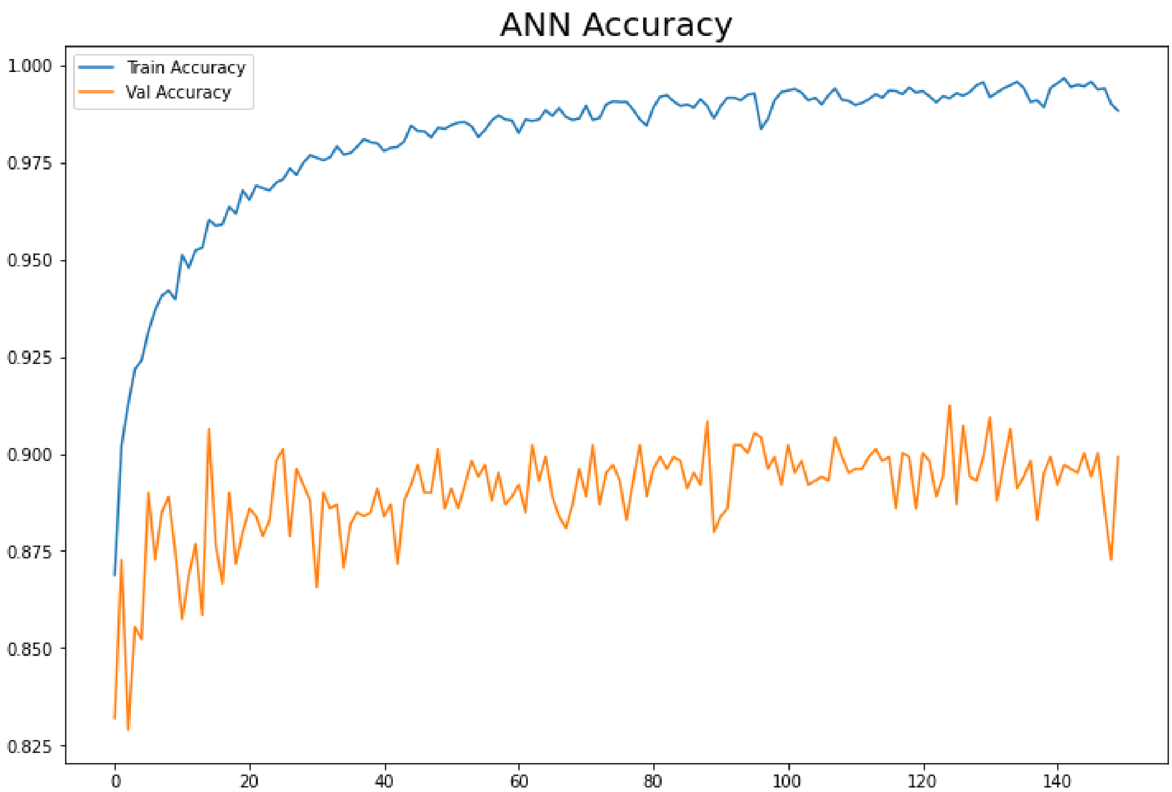
Out[175]:

```
Text(69.0, 0.5, 'Truth')
```



In [176]:

```
## Plot History
fig = plt.figure(figsize=(12, 8))
plt.title('ANN Accuracy', size=20)
plt.plot(history.history['accuracy'], label="Train Accuracy")
plt.plot(history.history['val_accuracy'], label="Val Accuracy")
plt.legend()
plt.savefig("Visualizations\ANNAccuracyGraph.png")
plt.show()
model.evaluate(X_test,y_test)
score = np.round(model.evaluate(X_test, y_test, verbose=0)[1], 3)
print(f'Neural Network score     ========>>> {score}')
models_resultsANN = ({
    'Model Name': 'Artificial Neural Network',
    'Model Score': score,
    'F1 Score': f1Score,
    'Precision Score': preScore,
    'Recall Score': recScore
})
```




```
31/31 [==============================] - 0s 1ms/step - loss: 1.2418 - accura
cy: 0.8992
Neural Network score     ========>>> 0.899
```

In [177]:

```
myalgorithms = {
    'Logistic Regression':models_resultsLR,
    'Gradient Boost': models_resultsGB,
    'Decision Tree': models_resultsDT,
    'Random Forest Classifier': models_resultsRC,
    'K Nearest Neighbour': models_resultsKN,
    'Artificial Neural Network': models_resultsANN
}
myalgorithms
```

Out[177]:

```
{'Logistic Regression': {'Model Name': 'Logistic Regression',
  'Model Score': 0.8360488798370672,
  'F1 Score': 0.15706806282722513,
  'Precision Score': 0.10067114093959731,
  'Recall Score': 0.35714285714285715},
 'Gradient Boost': {'Model Name': 'Gradient Boost',
  'Model Score': 0.9093686354378818,
  'F1 Score': 0.08247422680412371,
  'Precision Score': 0.07272727272727272,
  'Recall Score': 0.09523809523809523},
 'Decision Tree': {'Model Name': 'Decision Tree',
  'Model Score': 0.8686354378818737,
  'F1 Score': 0.1342281879194631,
  'Precision Score': 0.09345794392523364,
  'Recall Score': 0.23809523809523808},
 'Random Forest Classifier': {'Model Name': 'Random Forest',
  'Model Score': 0.9134419551934827,
  'F1 Score': 0.12371134020618557,
  'Precision Score': 0.10909090909090909,
  'Recall Score': 0.14285714285714285},
 'K Nearest Neighbour': {'Model Name': 'KNN',
  'Model Score': 0.869653767820774,
  'F1 Score': 0.15789473684210525,
  'Precision Score': 0.10909090909090909,
  'Recall Score': 0.2857142857142857},
 'Artificial Neural Network': {'Model Name': 'Artificial Neural Network',
  'Model Score': 0.899,
  'F1 Score': 0.5352046011961963,
  'Precision Score': 0.530086114933288,
  'Recall Score': 0.549290780141844}}
```

In [178]:

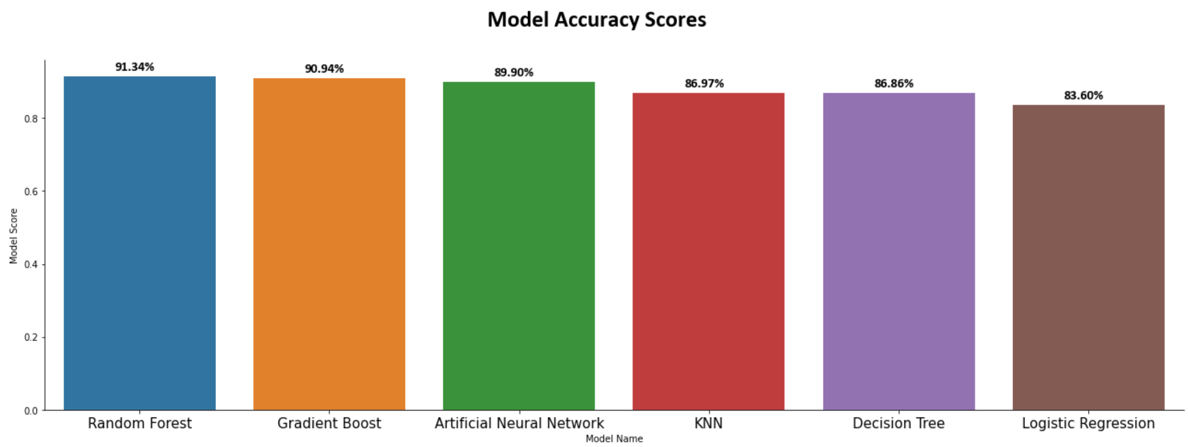
```
myalgorithmsdf = pd.DataFrame(myalgorithms.values(),columns=['Model Name','Model Score
myalgorithmsdf.sort_values(by='Model Score',ascending=False, inplace=True)
myalgorithmsdf
```

Out[178]:

	Model Name	Model Score	F1 Score	Precision Score	Recall Score
3	Random Forest	0.913442	0.123711	0.109091	0.142857
1	Gradient Boost	0.909369	0.082474	0.072727	0.095238
5	Artificial Neural Network	0.899000	0.535205	0.530086	0.549291
4	KNN	0.869654	0.157895	0.109091	0.285714
2	Decision Tree	0.868635	0.134228	0.093458	0.238095
0	Logistic Regression	0.836049	0.157068	0.100671	0.357143

In [179]:

```
g = sns.catplot(x='Model Name', y='Model Score', data=myalgorithmsdf,
                height=6, aspect=3, kind='bar', legend=True)
g.fig.suptitle('Model Accuracy Scores', size=25, y=1.1, **hfont)
ax = g.facet_axis(0,0)
ax.tick_params(axis='x', which='major', labelsize=15)
for p in ax.patches:
    ax.text(p.get_x() + 0.27,
            p.get_height() * 1.02,
           '{0:.2f}%'.format(p.get_height()*100),
            color='black',
            rotation='horizontal',
            size='x-large', **hfont)
plt.savefig("Visualizations\ModelAccuracy.png")
```



In [180]:

```
# From the above diagram, it shows that Random Forest is the best model to use for the
```

SHAP

In [181]:

```
import shap
```

SHAP with RandomForestClassifier

In [183]:

```
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,random_state=2)
sm = SMOTE(random_state=0)
X_train,y_train = sm.fit_resample(X_train,y_train)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

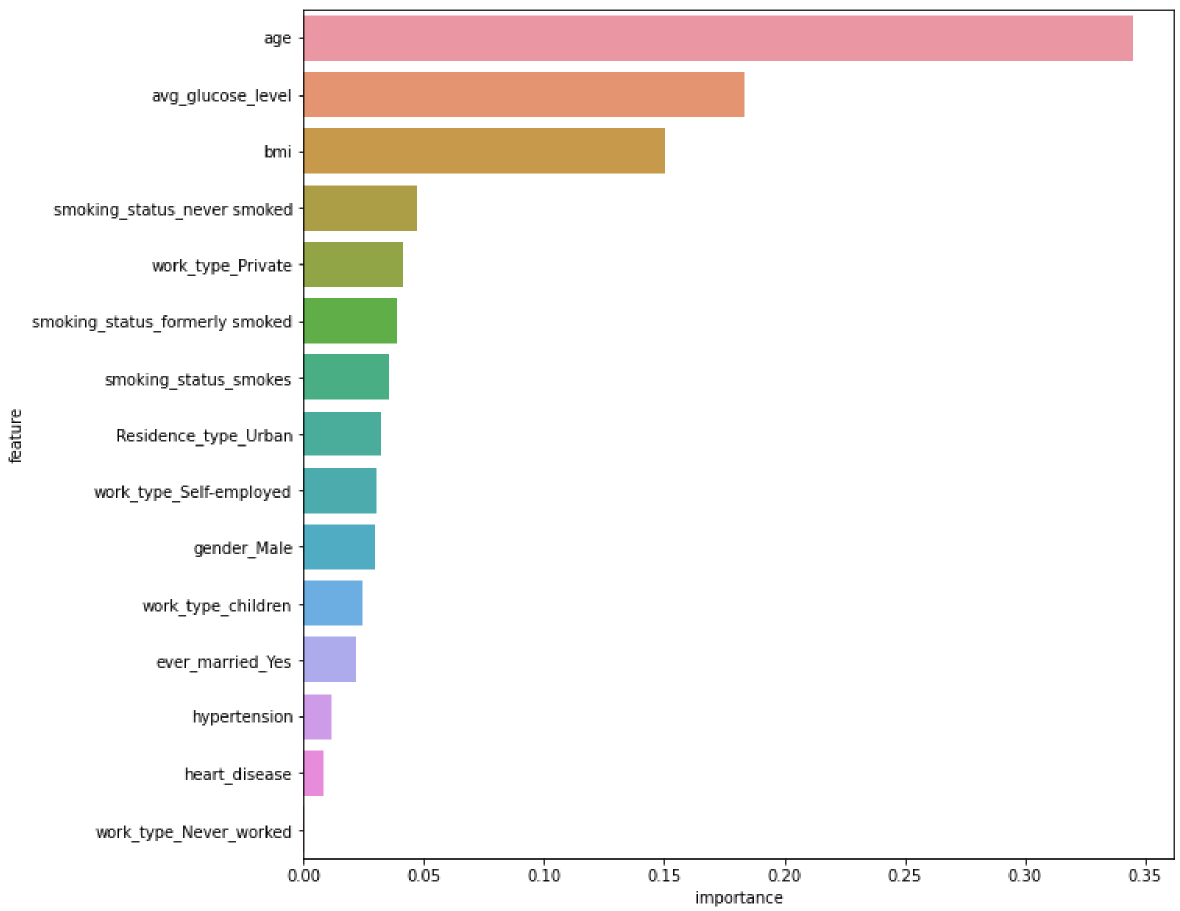
In [190]:

```
# Random Forest Feature Importance
```

In [185]:

```
RFModel = RandomForestClassifier(n_estimators=100,n_jobs=1)
RFModel.fit(X_train,y_train)
feature_importance_df = pd.DataFrame()
feature_importance_df['feature'] = X.columns
feature_importance_df['importance'] = RFModel.feature_importances_

feature_importance_df = feature_importance_df.sort_values('importance',ascending=False
print('***Random Forest***')
plt.figure(figsize=(10,10))
sns.barplot(x='importance',y='feature',data=feature_importance_df[:15])
plt.savefig("Visualizations\ShapValueRandomForest.png")
plt.show()
```

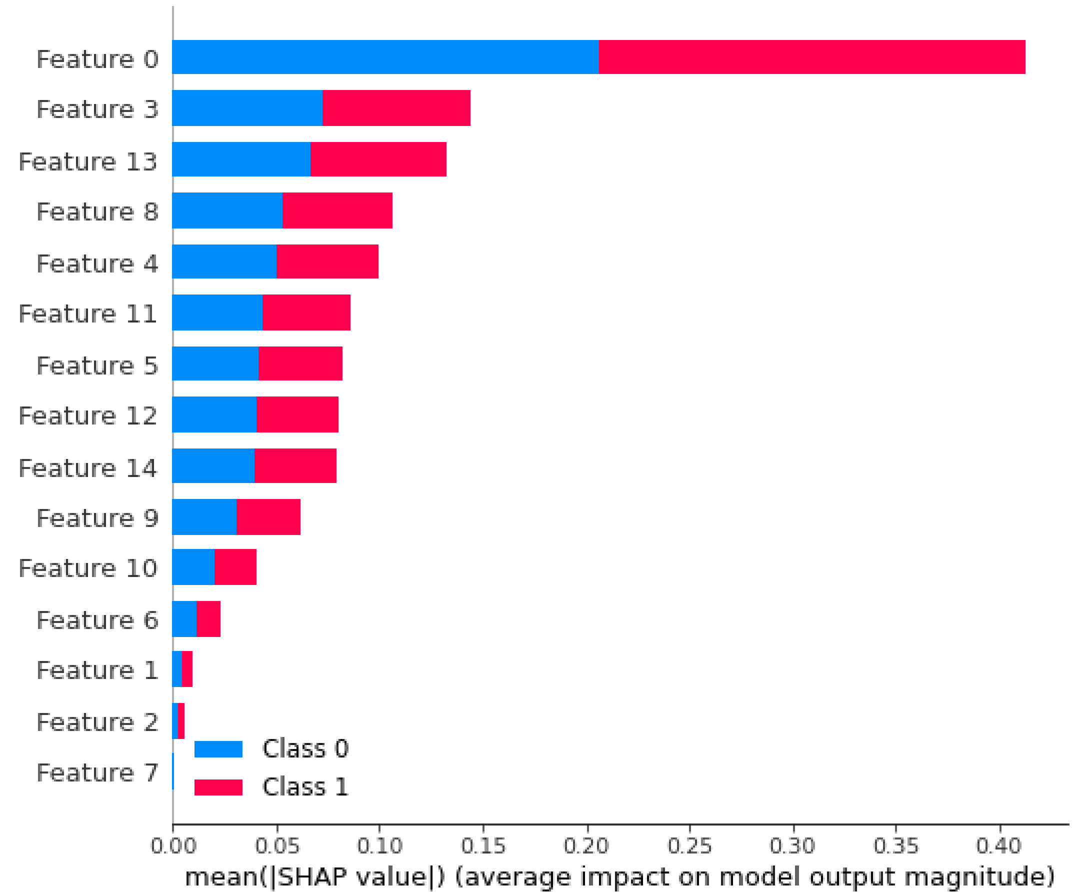
```
***Random Forest***
```



In [191]:

```
#Initialize SHAP Tree Explainer
explainer = shap.TreeExplainer(RFModel,model_output='margin')
shap_values = explainer.shap_values(X_test)

#Baseline Value
expected_value = explainer.expected_value
if isinstance(expected_value,list):
    expected_value = expected_value[1]

print(f'Explainer Expected Value: {expected_value}')
shap.summary_plot(shap_values,X_test)
```

```
Explainer Expected Value: [0.50111998 0.49888002]
```




```
<Figure size 432x288 with 0 Axes>
```

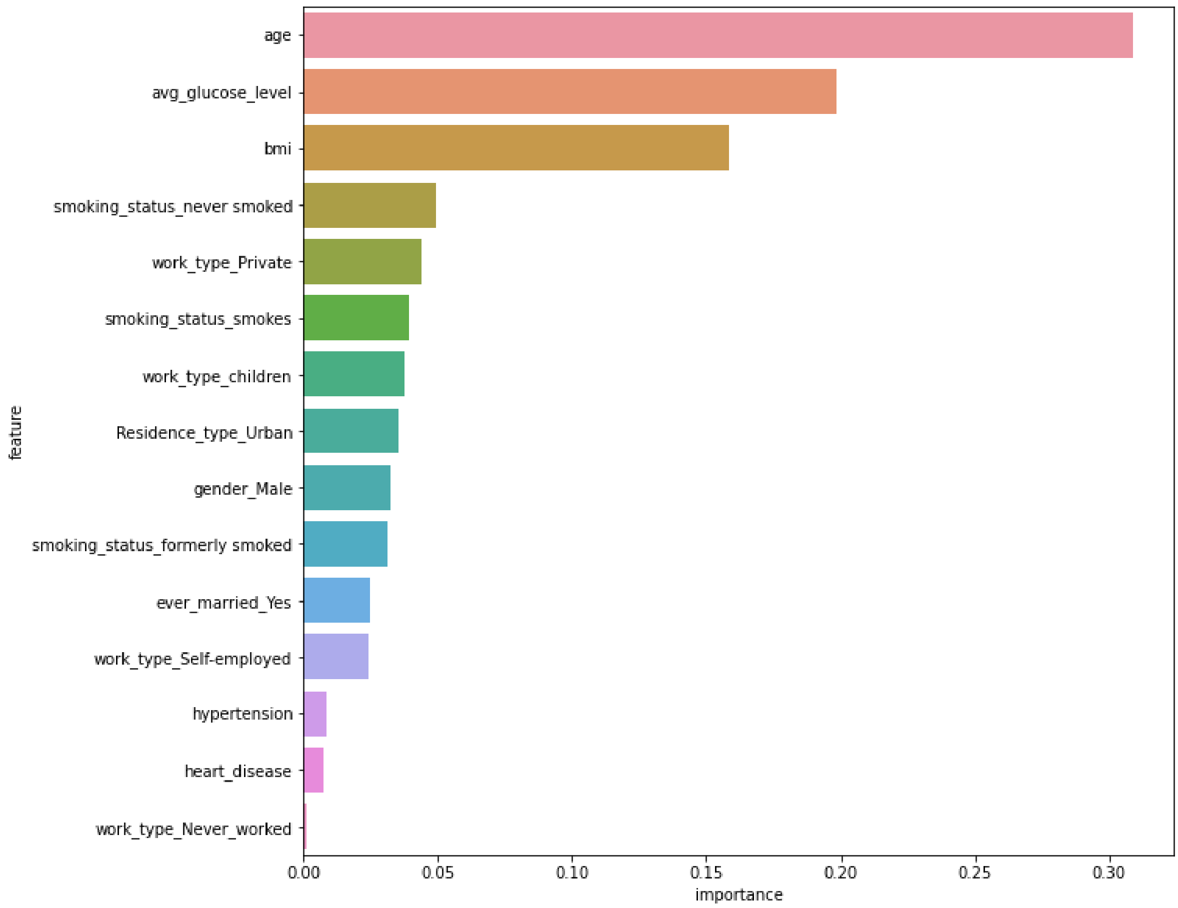
In [ ]:

```
# Gradient Boost Feature Importance
```

In [193]:

```
GBModel = GradientBoostingClassifier(learning_rate=0.01,loss='exponential',max_depth= !
GBModel.fit(X_train,y_train)
feature_importance_df = pd.DataFrame()
feature_importance_df['feature'] = X.columns
feature_importance_df['importance'] = GBModel.feature_importances_

feature_importance_df = feature_importance_df.sort_values('importance',ascending=False]
print('***Gradient Boost***')
plt.figure(figsize=(10,10))
sns.barplot(x='importance',y='feature',data=feature_importance_df[:15])
plt.savefig("Visualizations\ShapValueGradientBoost.png")
plt.show()
```

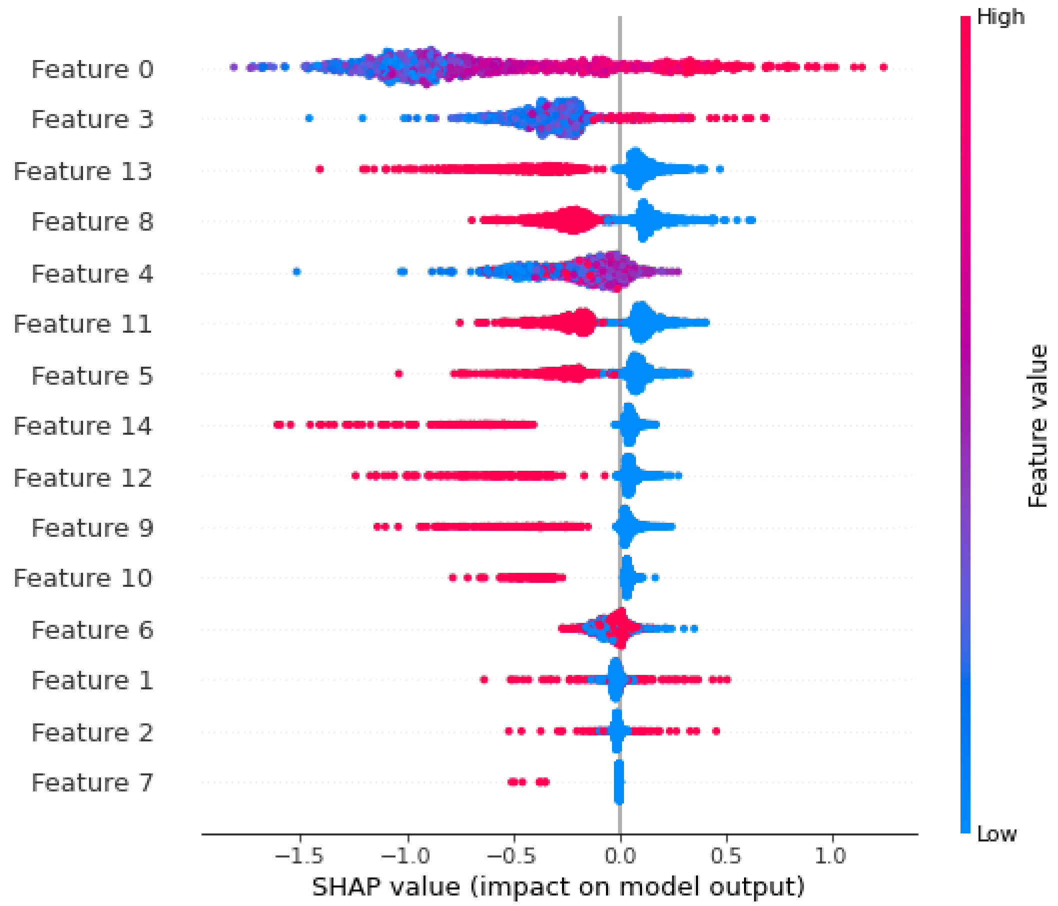
```
***Gradient Boost***
```



In [194]:

```python
#Initialize SHAP Tree Explainer
explainer = shap.TreeExplainer(GBModel,model_output='margin')
shap_values = explainer.shap_values(X_test)

#Baseline Value
expected_value = explainer.expected_value
if isinstance(expected_value,list):
    expected_value = expected_value[1]

print(f'Explainer Expected Value: {expected_value}')
shap.summary_plot(shap_values,X_test)
```

```
Explainer Expected Value: [8.28089334e-18]
```




```
<Figure size 432x288 with 0 Axes>
```

In [ ]:

```

```