Model Monitoring on Stroke Prediction Data

1.1 Importing Libraries:

In [76]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from imblearn.over_sampling import SMOTE
from sklearn.metrics import roc_auc_score
import warnings
warnings.filterwarnings("ignore")
from plotly.subplots import make_subplots
import plotly.express as px
from IPython.core.display import display, HTML, Javascript
from plotly.offline import download_plotlyjs,init_notebook_mode
init_notebook_mode(connected=True)
```

In [77]:
```
import alibi_detect
from alibi_detect.cd import ChiSquareDrift
```

1.2 Importing the Dataset:

In [78]:
```
# Load data into a pandas Dataframe
rawdata = pd.read_csv("C:/Users/rahul/Summer Project/Dataset/healthcare-dataset-stroke-data.csv")
# View first 5 rows in the Dataset
rawdata.head()
```

Out[78]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	9046	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked	1
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	NaN	never smoked	1
2	31112	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never smoked	1
3	60182	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smokes	1
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never smoked	1

In [79]:
```
# View last 5 rows in the Dataset
rawdata.tail()
```

Out[79]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
5105	18234	Female	80.0	1	0	Yes	Private	Urban	83.75	NaN	never smoked	0
5106	44873	Female	81.0	0	0	Yes	Self-employed	Urban	125.20	40.0	never smoked	0
5107	19723	Female	35.0	0	0	Yes	Self-employed	Rural	82.99	30.6	never smoked	0
5108	37544	Male	51.0	0	0	Yes	Private	Rural	166.29	25.6	formerly smoked	0
5109	44679	Female	44.0	0	0	Yes	Govt_job	Urban	85.28	26.2	Unknown	0

In [80]:
```
rawdata.describe()
```

Out[80]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	stroke
count	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	4909.000000	5110.000000
mean	36517.829354	43.226614	0.097456	0.054012	106.147677	28.893237	0.048728
std	21161.721625	22.612647	0.296607	0.226063	45.283560	7.854067	0.215320
min	67.000000	0.080000	0.000000	0.000000	55.120000	10.300000	0.000000
25%	17741.250000	25.000000	0.000000	0.000000	77.245000	23.500000	0.000000
50%	36932.000000	45.000000	0.000000	0.000000	91.885000	28.100000	0.000000
75%	54682.000000	61.000000	0.000000	0.000000	114.090000	33.100000	0.000000
max	72940.000000	82.000000	1.000000	1.000000	271.740000	97.600000	1.000000

1.3 Dataset Description

There are 12 columns in the dataset namely :

1) **id**: unique identifier

2) **gender**: with 3 categories - "Male", "Female" and "Other"

3) **age**: age of the individual

4) **hypertension**: with 2 categories -'0' and '1'; 0 if the patient doesn't have hypertension, 1 if the patient has hypertension

5) **heart_disease**: with 2 categories0 -'0' and '1'; 0 if the patient doesn't have any heart diseases, 1 if the patient has a heart disease

6) **ever_married**: with 2 categories -"No" and "Yes"

7) **work_type**: with 5 categories -"children", "Govt_jov", "Never_worked", "Private" and "Self-employed"

8) **Residence_type**: with 2 categories - "Rural" and "Urban"

9) **avg_glucose_level**: average glucose level in blood

10) **bmi**: Body Mass Index of the individual

11) **smoking_status**: with 4 categories - "formerly smoked", "never smoked", "smokes" or "Unknown"*

12) **stroke**: with 2 categories -'0' and '1'; 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

2. Data Cleansing Task:

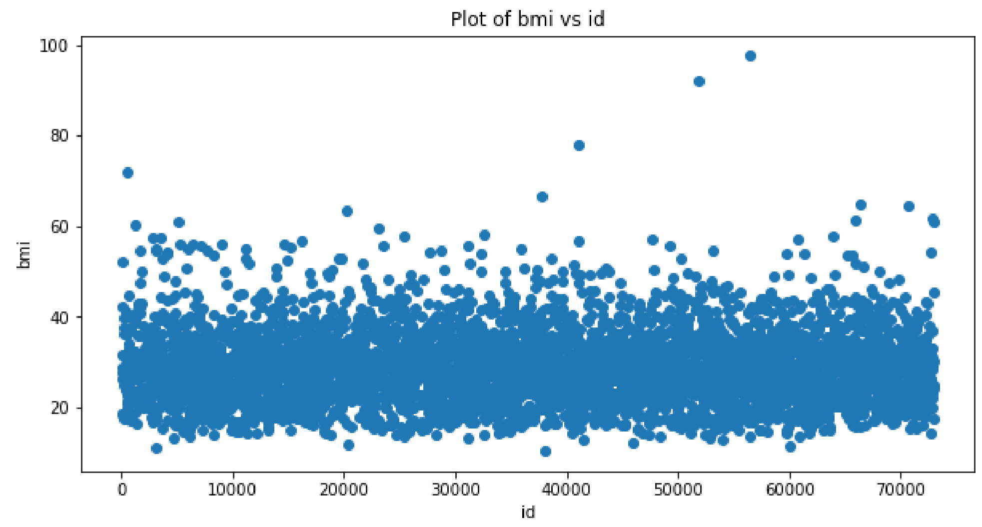
In [81]:
```
#explore missing values
rawdata.isna().sum()
```

Out[81]:
```
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
```

Handling missing values

There are 201 missing values in the variable 'bmi'. A graph will be plotted for visualising the data and to solve the problem.

In [82]:
```
x=rawdata["id"]
y=rawdata["bmi"]
plt.figure(figsize = (10,5))
plt.scatter(x,y)
plt.xlabel('id')
plt.ylabel('bmi')
plt.title('Plot of bmi vs id')
plt.show()
```



From the above graph, it is evident that there are only a few outliers in the observations of the variable 'bmi' and most of the values of the varible are concentrated around the range 20 to 40. So we perform 'Mean Imputation' here i.e. impute the missing values by the arithmetic mean of the available observations.

In [83]:
```python
# Replace NA values in 'bmi' column with mean of column (bmi) values
rawdata['bmi'].fillna(rawdata['bmi'].mean(), inplace=True)
# Check whether there is any missing value left in our data
rawdata.isna().sum()
```

Out[83]:
```
id                   0
gender               0
age                  0
hypertension         0
heart_disease        0
ever_married         0
work_type            0
Residence_type       0
avg_glucose_level    0
bmi                  0
smoking_status       0
stroke               0
dtype: int64
```

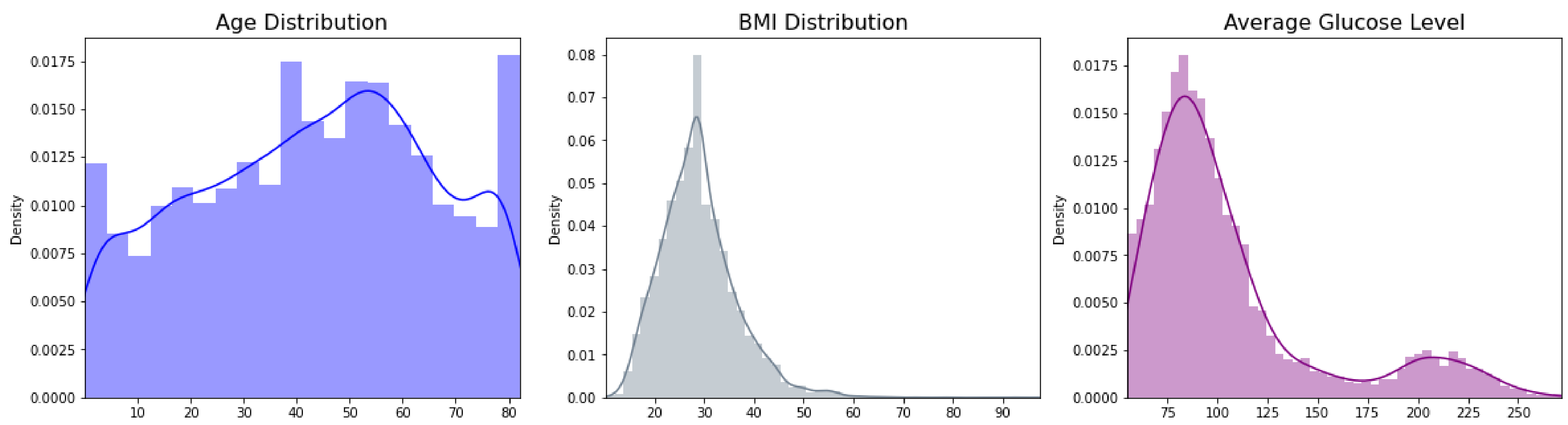
3. Exploratory Data Analysis (EDA) :

In [84]:
```python
# Define continuous and categorical data columns.
all_columns = list(rawdata.columns)
categorical_data_cols  = [column for column in all_columns if len(rawdata[column].unique())<=5]
continuous_data_cols  = [column for column in all_columns if column not in categorical_data_cols]
print(f"Continuos Data Columns: {', '.join(continuous_data_cols)}")
print(f"Categorical Data Columns: {', '.join(categorical_data_cols)}")
```

```
Continuos Data Columns: id, age, avg_glucose_level, bmi
Categorical Data Columns: gender, hypertension, heart_disease, ever_married, work_type, Residence_type, smoking_status, stroke
```

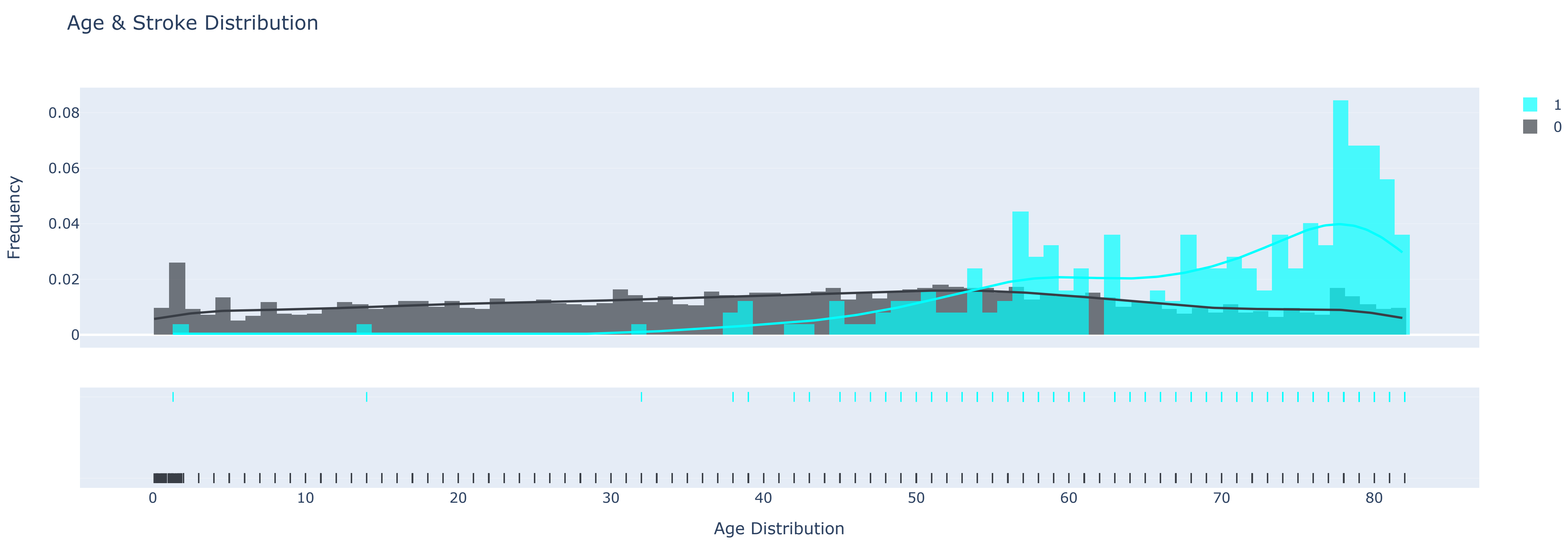
3.1. Visualization of Continuous Data:

In [85]:
```python
fig = plt.figure(figsize=(20,5))
continuous_data = ["age","bmi","avg_glucose_level"]

plt.subplot(1,3,1)
att = rawdata["age"].values
p = sns.distplot(att,color="blue")
p.set_title("Age Distribution",fontsize=16)
p.set_xlim([min(att),max(att)])

plt.subplot(1,3,2)
att = rawdata["bmi"].values
p = sns.distplot(att,color="slategrey")
p.set_title("BMI Distribution",fontsize=16)
p.set_xlim([min(att),max(att)])

plt.subplot(1,3,3)
att =rawdata["avg_glucose_level"].values
p = sns.distplot(att,color="purple")
p.set_title("Average Glucose Level",fontsize=16)
p.set_xlim([min(att),max(att)])
plt.show()
```



From the above plots we can see that the Age distribution is close to symmetric and the other two distributions are positively skewed.

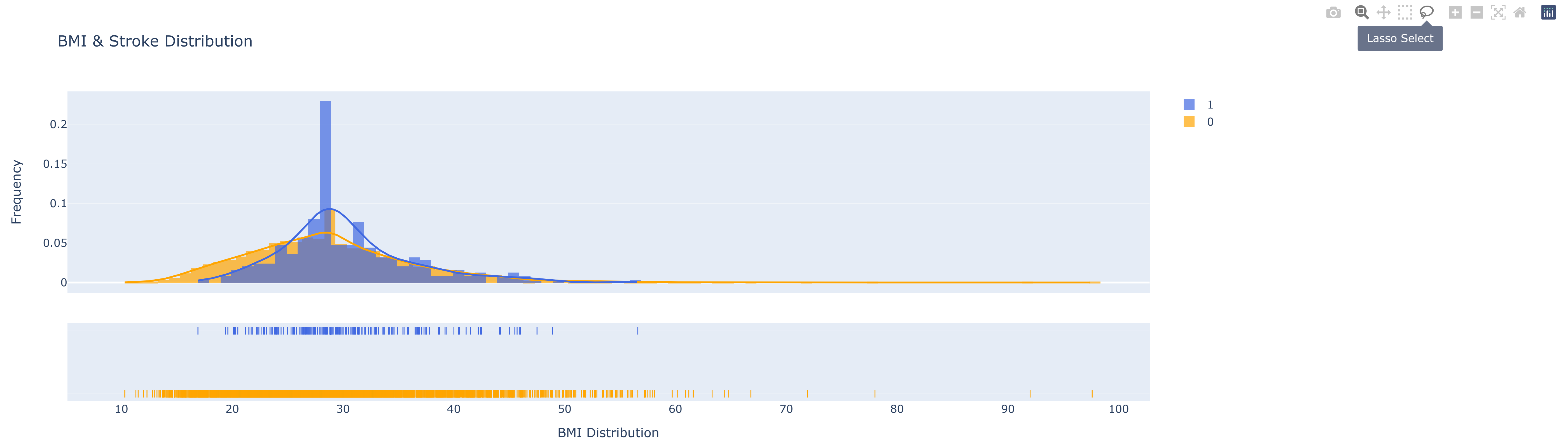
In [86]:
```python
import plotly.figure_factory as ff
group_labels = ['0', '1']
l = [rawdata['age'][(rawdata["stroke"] == 0)],rawdata['age'][(rawdata["stroke"] == 1)]]
fig = ff.create_distplot(l, group_labels,curve_type='kde',colors = ['#393E46', 'cyan'])
fig.update_layout(title_text='Age & Stroke Distribution',xaxis_title="Age Distribution",yaxis_title="Frequency")
fig.show()
```



Observations:

- We can infer that after the age of 40 the risk of Stroke increases.
- At the age above 76 there is high chance of stroke.

In [87]:
```python
import plotly.figure_factory as ff
group_labels = ['0', '1']
l = [rawdata['bmi'][(rawdata["stroke"] == 0)],rawdata['bmi'][(rawdata["stroke"] == 1)]]
fig = ff.create_distplot(l, group_labels,curve_type='kde',colors = ['orange', 'royalblue'])
fig.update_layout(title_text='BMI & Stroke Distribution',xaxis_title="BMI Distribution",yaxis_title="Frequency")
fig.show()
```



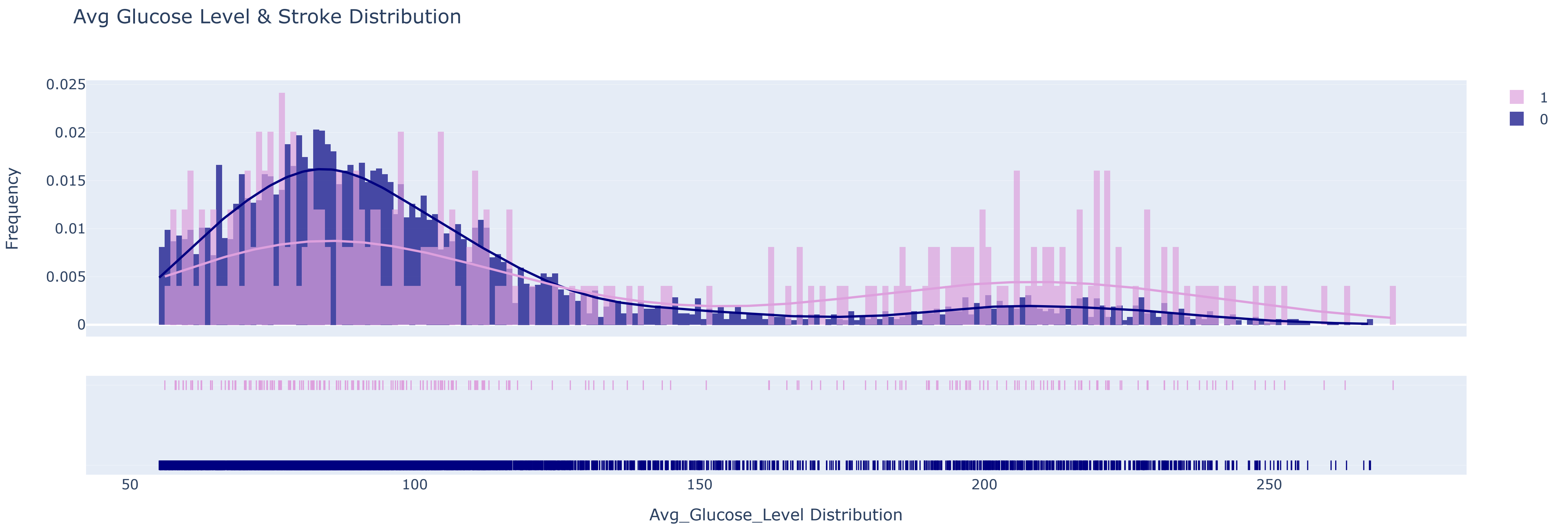
Observations:

The World Health Organisation classifies an individual according to BMI as follows :

- Below 18.5 - Underweight
- 18.5-24.9 - Normal
- 25.0-29.9 - Overweight
- 30.0 And Above - Obese

From the above plot we can observe that individuals with BMI 25 and above are more likely to have a stroke, hence the chance of stroke is more in overweight and obese people.

In [88]:
```
import plotly.figure_factory as ff
group_labels = ['0', '1']
l = [rawdata['avg_glucose_level'][(rawdata["stroke"] == 0)],rawdata['avg_glucose_level'][(rawdata["stroke"] == 1)]]
fig = ff.create_distplot(l, group_labels,curve_type='kde',colors = ['navy', 'plum'])
fig.update_layout(title_text='Avg Glucose Level & Stroke Distribution',xaxis_title="Avg_Glucose_Level Distribution",yaxis_title="Frequency")
fig.show()
```

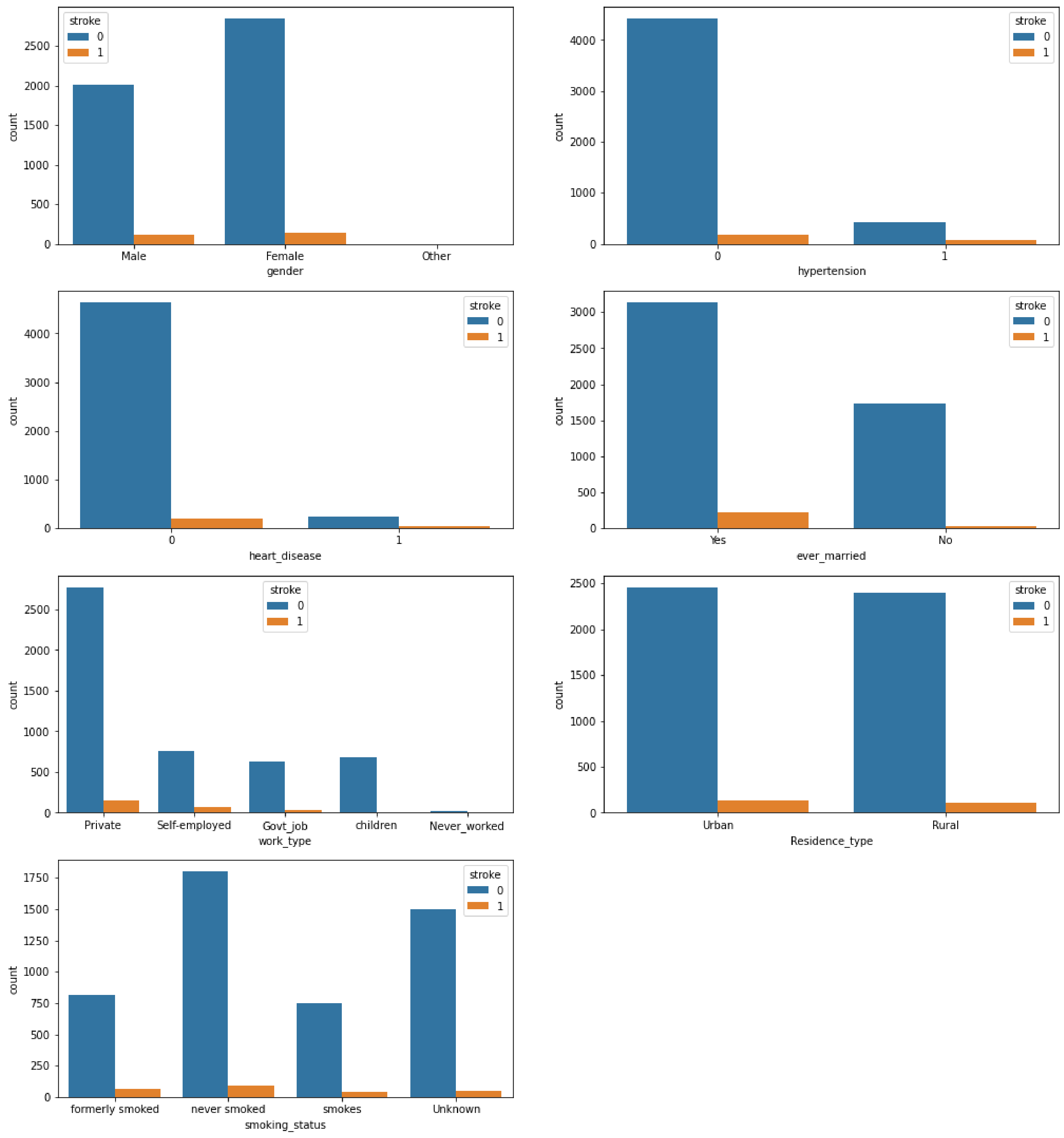


Observations:

- Elevated glucose level results in higher chances of a stroke, a trait observed in diabetic patients.
- From the graph we can infer that above the level of 150/160, the risk of stroke increases.

3.2. Visualization of Categorical Data:

In [89]:
```
plt.figure(figsize = (17,19))
i = 1
for column in categorical_data_cols[:-1]:
    plt.subplot(4, 2, i)
    sns.countplot(x =rawdata[column], hue = rawdata["stroke"])
    i+=1
plt.show()
```

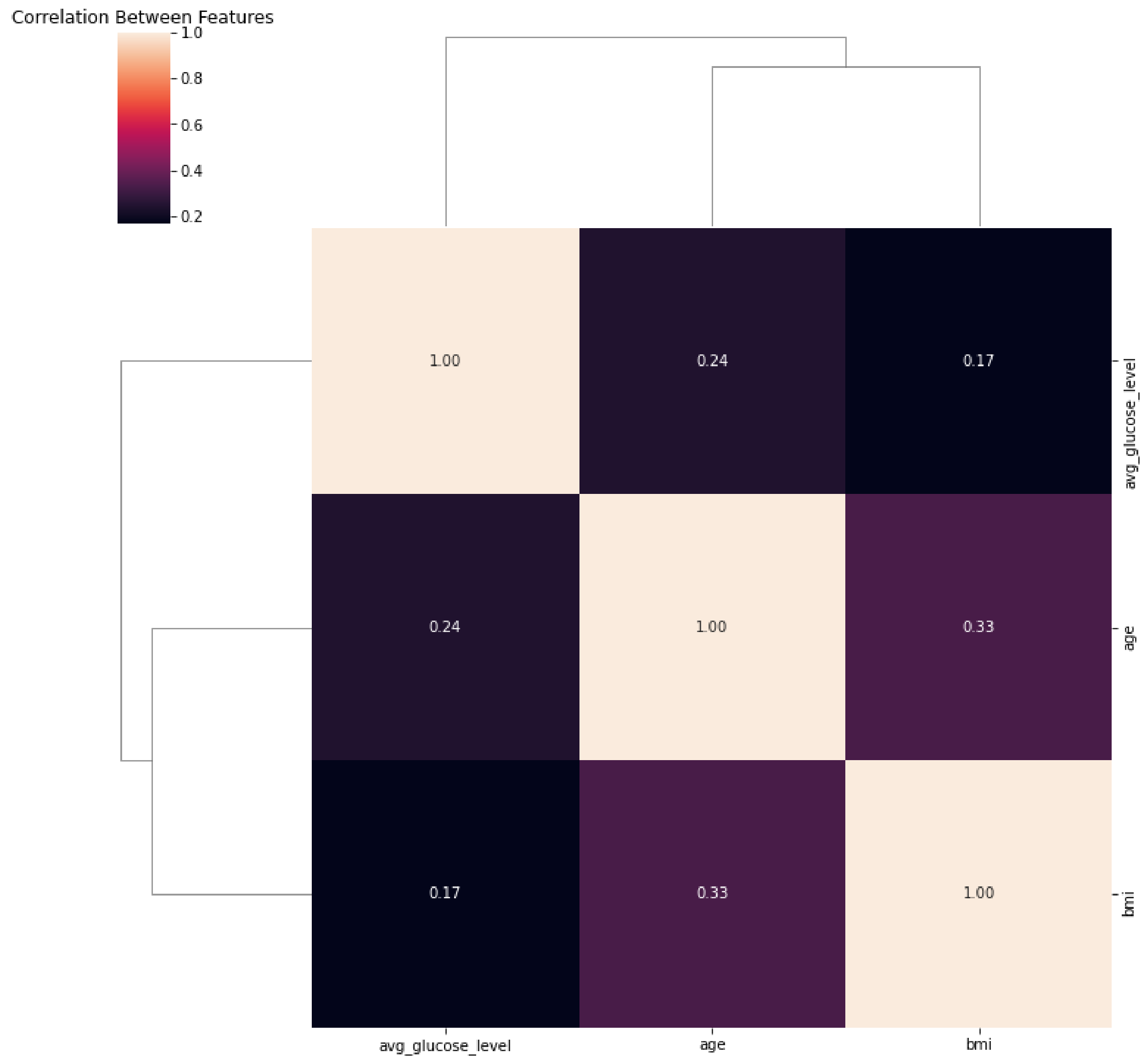


Observations:

- The number of male and female having stroke are almost equal in number.
- The people suffering and not suffering with hypertension have almost same and no sign of stroke. This may be due to the fact that the number of records with stroke "1" is very less.
- The proportion of people who had a stroke in the heart_disease category is much higher than the proportion of people who had a stroke in the No heart_disease category.
- The married people are showing more signs for stroke.
- The people who are having private jobs are more prone to stroke.
- The likelihood of having a stroke is the same for living in an urban region and in a rural region.
- smoking_status does not have much influence on the probability of having a stroke.

3.3. Correlation Plot:

In [90]:
```
rdata=rawdata.drop(['id']+['hypertension']+['stroke']+['heart_disease'],axis=1)
corr_data = rdata.corr() # It checks the correlation between the numerical values in the data.
sns.clustermap(corr_data,annot= True,fmt = '.2f')
# While annot shows the numerical values on the chart, fmt determines how many digits will be displayed after the comma.

plt.title('Correlation Between Features')
plt.show();
```



From the above correlation plot, it is quite evident that there is almost no correlation among the continuous features.

4. Data preprocessing :

In [91]:
```
# Shuffle the rows of the dataset for future purposes
data = rawdata.sample(frac=1,random_state=4).reset_index(drop=True)
```

In [92]:
```
data.head()
```

Out[92]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	58007	Female	36.0	0	0	Yes	Private	Urban	87.88	34.7	smokes	0
1	4528	Male	45.0	1	0	No	Private	Rural	85.52	36.4	never smoked	0
2	61715	Male	55.0	0	0	Yes	Private	Rural	56.42	31.8	never smoked	0
3	875	Female	34.0	0	0	No	Private	Urban	67.66	22.4	never smoked	0
4	54869	Female	30.0	0	0	Yes	Private	Urban	116.98	26.0	never smoked	0

In [93]:
```
data.tail()
```

Out[93]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
5105	37038	Male	15.0	0	0	No	children	Urban	95.86	18.100000	Unknown	0
5106	49086	Female	23.0	0	0	No	Private	Urban	60.50	27.100000	formerly smoked	0
5107	44325	Male	78.0	0	0	Yes	Self-employed	Rural	126.39	21.300000	smokes	0
5108	40899	Female	78.0	0	0	Yes	Self-employed	Rural	60.67	28.893237	formerly smoked	1
5109	50371	Male	56.0	0	0	Yes	Private	Urban	63.18	31.500000	Unknown	0

Encoding Categorical Features with One-Hot Encoder :

In [94]:

```
# Categorical Columns: 'gender', 'ever_married', 'work_type', 'Residence_type', 'smoking_status'
from sklearn.preprocessing import OneHotEncoder

# Initialize One Hot Encoder
one_hot_encoder = OneHotEncoder()
# Fit and Transform the columns
data_temp = one_hot_encoder.fit_transform(data[['gender', 'ever_married', 'work_type', 'Residence_type', 'smoking_status']]).toarray()

# Get newly encoded columns and concat them to the Dataframe
encodings = pd.DataFrame(columns = one_hot_encoder.get_feature_names_out(),data = data_temp)
encodings = encodings.astype(int)
data = pd.concat([data,encodings] , axis=1)
Stroke=data['stroke']

# Drop original columns from the dataset after encoding is done
data.drop(['gender', 'ever_married', 'work_type', 'Residence_type', 'smoking_status','stroke'],axis = 1, inplace=True)
data=pd.concat([data,Stroke],axis=1)
data.head()
```

Out[94]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	gender_Female	gender_Male	gender_Other	ever_married_No	...	work_type_Private	work_type_Self-employed	work_type_children	Residence_type_Rural	Residence_type_Urban	smoking_status_Unknown	smoking_status_formerly smoked	sm
0	58007	36.0	0	0	87.88	34.7	1	0	0	0	...	1	0	0	0	1	0	0	
1	4528	45.0	1	0	85.52	36.4	0	1	0	1	...	1	0	0	1	0	0	0	
2	61715	55.0	0	0	56.42	31.8	0	1	0	0	...	1	0	0	1	0	0	0	
3	875	34.0	0	0	67.66	22.4	1	0	0	1	...	1	0	0	0	1	0	0	
4	54869	30.0	0	0	116.98	26.0	1	0	0	0	...	1	0	0	0	1	0	0	

5 rows × 23 columns

In [95]:

```
data.tail()
```

Out[95]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	gender_Female	gender_Male	gender_Other	ever_married_No	...	work_type_Private	work_type_Self-employed	work_type_children	Residence_type_Rural	Residence_type_Urban	smoking_status_Unknown	smoking_status_form smo
5105	37038	15.0	0	0	95.86	18.100000	0	1	0	1	...	0	0	1	0	1	1	
5106	49086	23.0	0	0	60.50	27.100000	1	0	0	1	...	1	0	0	0	1	0	
5107	44325	78.0	0	0	126.39	21.300000	0	1	0	0	...	0	1	0	1	0	0	
5108	40899	78.0	0	0	60.67	28.893237	1	0	0	0	...	0	1	0	1	0	0	
5109	50371	56.0	0	0	63.18	31.500000	0	1	0	0	...	1	0	0	0	1	1	

5 rows × 23 columns

In [96]:

```
data.describe()
```

Out[96]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	gender_Female	gender_Male	gender_Other	ever_married_No	...	work_type_Private	work_type_Self-employed	work_type_children	Residence_type_Rural	Residence_type_Urban	smoking_status_Unknown	sm
count	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	...	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	
mean	36517.829354	43.226614	0.097456	0.054012	106.147677	28.893237	0.585910	0.413894	0.000196	0.343836	...	0.572407	0.160274	0.134442	0.491977	0.508023	0.302153	
std	21161.721625	22.612647	0.296607	0.226063	45.283560	7.698018	0.492612	0.492578	0.013989	0.475034	...	0.494778	0.366896	0.341160	0.499985	0.499985	0.459236	
min	67.000000	0.080000	0.000000	0.000000	55.120000	10.300000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	17741.250000	25.000000	0.000000	0.000000	77.245000	23.800000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	36932.000000	45.000000	0.000000	0.000000	91.885000	28.400000	1.000000	0.000000	0.000000	0.000000	...	1.000000	0.000000	0.000000	0.000000	1.000000	0.000000	
75%	54682.000000	61.000000	0.000000	0.000000	114.090000	32.800000	1.000000	1.000000	0.000000	1.000000	...	1.000000	0.000000	0.000000	1.000000	1.000000	1.000000	
max	72940.000000	82.000000	1.000000	1.000000	271.740000	97.600000	1.000000	1.000000	1.000000	1.000000	...	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	

8 rows × 23 columns

In [97]:

```
#Exporting the one hot encoded dataset as a csv file in local drive
exceldata=data.to_csv("C:\\Users\\rahul\\Summer Project\\Dataset\\healthcare-dataset-stroke-data-after-one-hot-encoding.csv",index=False)
```

5. Splitting the dataset :

Now we will split the data into six parts viz. train data (approx 60%), test data (approx 10%), live dataset1 (10%), live dataset2 (10%), live dataset3 (10%).

In [98]:

```
train_data=data.iloc[:3070]
test_data=data.iloc[3070:3577]
l1=data.iloc[3577:4088]
l2=data.iloc[4088:4599]
l3=data.iloc[4599:]
```

5.1. Showing the first and last rows of each of the splitted datasets:

In [99]:

```
train_data.head(1)
```

Out[99]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	gender_Female	gender_Male	gender_Other	ever_married_No	...	work_type_Private	work_type_Self-employed	work_type_children	Residence_type_Rural	Residence_type_Urban	smoking_status_Unknown	smoking_status_formerly smoked	sm
0	58007	36.0	0	0	87.88	34.7	1	0	0	0	...	1	0	0	0	1	0	0	

1 rows × 23 columns

In [100…

```
train_data.tail(1)
```

Out[100]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	gender_Female	gender_Male	gender_Other	ever_married_No	...	work_type_Private	work_type_Self-employed	work_type_children	Residence_type_Rural	Residence_type_Urban	smoking_status_Unknown	smoking_status_formerly smoked
3069	55459	60.0	0	0	91.82	28.3	1	0	0	1	...	1	0	0	1	0	0	1

1 rows × 23 columns

In [101…

```
test_data.head(1)
```

Out[101]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	gender_Female	gender_Male	gender_Other	ever_married_No	...	work_type_Private	work_type_Self-employed	work_type_children	Residence_type_Rural	Residence_type_Urban	smoking_status_Unknown	smoking_status_formerly smoked
3070	6048	65.0	0	0	104.12	27.4	1	0	0	0	...	1	0	0	0	1	0	0

1 rows × 23 columns

In [102…

```
test_data.tail(1)
```

Out[102]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	gender_Female	gender_Male	gender_Other	ever_married_No	...	work_type_Private	work_type_Self-employed	work_type_children	Residence_type_Rural	Residence_type_Urban	smoking_status_Unknown	smoking_status_formerly smoked
3576	50001	34.0	0	0	86.36	32.1	1	0	0	0	...	0	0	0	1	0	0	0

1 rows × 23 columns

In [103…

```
l1.head(1)
```

Out[103]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	gender_Female	gender_Male	gender_Other	ever_married_No	...	work_type_Private	work_type_Self-employed	work_type_children	Residence_type_Rural	Residence_type_Urban	smoking_status_Unknown	smoking_status_formerly smoked
3577	10445	54.0	0	0	81.78	27.3	0	1	0	0	...	0	0	0	1	0	1	0

1 rows × 23 columns

In [104…
```
l1.tail(1)
```
Out[104]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	gender_Female	gender_Male	gender_Other	ever_married_No	...	work_type_Private	work_type_Self-employed	work_type_children	Residence_type_Rural	Residence_type_Urban	smoking_status_Unknown	smoking_status_formerly smoked
4087	24257	4.0	0	0	90.42	16.2	0	1	0	1	...	0	0	1	1	0	1	0

1 rows × 23 columns

In [105…
```
l2.head(1)
```
Out[105]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	gender_Female	gender_Male	gender_Other	ever_married_No	...	work_type_Private	work_type_Self-employed	work_type_children	Residence_type_Rural	Residence_type_Urban	smoking_status_Unknown	smoking_status_formerly smoked
4088	65946	53.0	0	0	123.87	28.8	0	1	0	0	...	1	0	0	1	0	1	0

1 rows × 23 columns

In [106…
```
l2.tail(1)
```
Out[106]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	gender_Female	gender_Male	gender_Other	ever_married_No	...	work_type_Private	work_type_Self-employed	work_type_children	Residence_type_Rural	Residence_type_Urban	smoking_status_Unknown	smoking_status_formerly smoked
4598	37413	39.0	0	0	77.54	32.7	1	0	0	0	...	1	0	0	0	1	1	0

1 rows × 23 columns

In [107…
```
l3.head(1)
```
Out[107]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	gender_Female	gender_Male	gender_Other	ever_married_No	...	work_type_Private	work_type_Self-employed	work_type_children	Residence_type_Rural	Residence_type_Urban	smoking_status_Unknown	smoking_status_formerly smoked
4599	35332	63.0	0	0	93.24	28.8	1	0	0	0	...	1	0	0	1	0	0	0

1 rows × 23 columns

In [108…
```
l3.tail(1)
```
Out[108]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	gender_Female	gender_Male	gender_Other	ever_married_No	...	work_type_Private	work_type_Self-employed	work_type_children	Residence_type_Rural	Residence_type_Urban	smoking_status_Unknown	smoking_status_formerly smoked
5109	50371	56.0	0	0	63.18	31.5	0	1	0	0	...	1	0	0	0	1	1	0

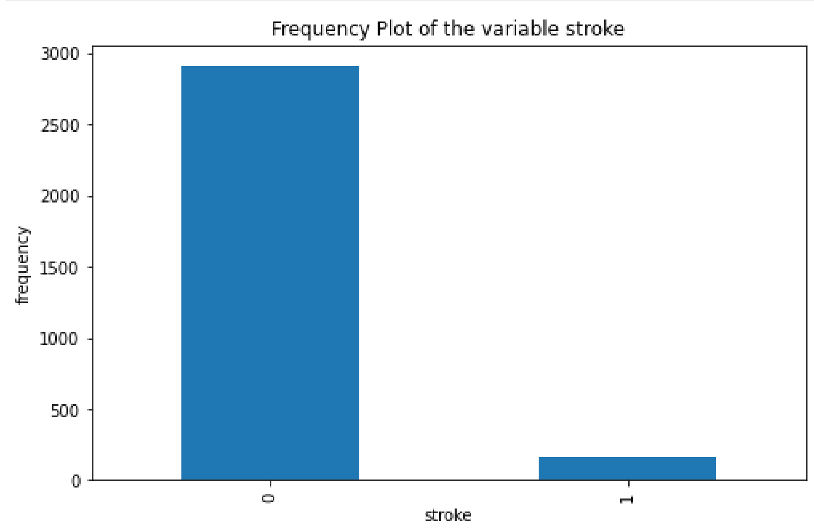
1 rows × 23 columns

6. Checking presence of data imbalance in train data:

In [109…
```
#Showing the count of the no. of persons who had a stroke
train_data['stroke'].value_counts()
```
Out[109]:
```
0    2913
1     157
Name: stroke, dtype: int64
```

We make a frequency plot of the target variable 'stroke' to show the data imbalance in the dataset visually.

In [110…
```
#Visualising the frequency plot
plt.figure(figsize = (8,5))
train_data['stroke'].value_counts().plot(kind='bar')
plt.xlabel('stroke')
plt.ylabel('frequency')
plt.title('Frequency Plot of the variable stroke')
plt.show()
```



Clearly, there is a data imbalance in our train data. So we will use SMOTE for solving this problem.

7. Training the model using different classifiers and K-fold cross-validation:

Here we will train our model using *Logistic Regression, Support Vector Classifier, Random Forest* and *K-Nearest Neighbour* (KNN) Algorithm. We will validate our model by **K-fold cross Validation** choosing **K=10** and taking **AUC(Area Under Curve)** score as the measure of performance of the models. We will perform **SMOTE(Synthetic Minority Oversampling Technique)** on train data sets, each of the times of fitting the models.

In [111…
```
#creating 10 parts of our dataset
N=3070
for i in range(1,11):
    globals()['d%s' % i] =  train_data.iloc[(i-1)*(N//10):i*(N//10)]
```

In [112…
```
#creating empty lists to store AUC scores for different models in K-fold cross-validation
lr_auc=[]
svc_auc=[]
rfc_auc=[]
knn_auc=[]
```

In [113…
```
#Model Fitting
L=[d1,d2,d3,d4,d5,d6,d7,d8,d9,d10]
for i in L:
    #creating train and validation datasets for each iteration
    val=i
    train=pd.concat([train_data, val]).drop_duplicates(keep=False)
    #Splitting the train dataset into feature vectors and target vector
    trainY=train['stroke']
    trainX=train.drop(['stroke']+['id'],axis=1)
    #performing SMOTE
    smote=SMOTE(k_neighbors=1)
    trainX_smote,trainY_smote=smote.fit_resample(trainX,trainY)
    # 7.1 Fitting logistic Regression Model
    from sklearn.linear_model import LogisticRegression
    lr=LogisticRegression()
    lr.fit(trainX_smote,trainY_smote)
    # 7.2 Fitting SVC
    from sklearn.svm import SVC
    svc=SVC(random_state = 87,probability=True)
    svc.fit(trainX_smote,trainY_smote)
    # 7.3 Fitting Random Forest Classifier
    from sklearn.ensemble import RandomForestClassifier
    rfc = RandomForestClassifier(random_state=87)
    rfc.fit(trainX_smote,trainY_smote)
    # 7.4 Fitting KNN Classifier
    from sklearn.neighbors import KNeighborsClassifier
    knn = KNeighborsClassifier(n_neighbors = 10)
    knn.fit(trainX_smote,trainY_smote)
    #Splitting the validation dataset into feature vectors and target vector
    valY=val['stroke']
    valX=val.drop(['stroke']+['id'],axis=1)
    # 8.1 Classification using Logistic Regression
    lr_pred_val = lr.predict(valX)
    # 8.2 Classification using SVC
    svc_pred_val = svc.predict(valX)
    # 8.3 Classification using Random Forest Classifier
    rfc_pred_val = rfc.predict(valX)
    # 8.4 Classification using KNN Classifier
    knn_pred_val = knn.predict(valX)
    #Storing AUC scores
    lr_auc.append(roc_auc_score(valY,lr_pred_val))
    svc_auc.append(roc_auc_score(valY,svc_pred_val))
```

```python
    rfc_auc.append(roc_auc_score(valY,rfc_pred_val))
    knn_auc.append(roc_auc_score(valY,knn_pred_val))
```

In [114…
```python
#Showing the average AUC scores of the different models
import statistics
print(f"The average AUC score of the Logistic model is        {statistics.mean(lr_auc)}")
print(f"The average AUC score of the SVC  model is            {statistics.mean(svc_auc)}")
print(f"The average AUC score of the Random Forest model is   {statistics.mean(rfc_auc)}")
print(f"The average AUC score of the KNN model is             {statistics.mean(knn_auc)}")
```

```
The average AUC score of the Logistic model is        0.5367535441300085
The average AUC score of the SVC  model is            0.7386153110611822
The average AUC score of the Random Forest model is   0.5084098002288808
The average AUC score of the KNN model is             0.6810130436058963
```

> Note that the average AUC score of SVC is highest among the six models. So, we will finally fit SVC over the entire train data set.

In [115…
```python
#Splitting the train dataset into feature vectors and target vector
train_Y=train_data['stroke']
train_X=train_data.drop(['stroke']+['id'],axis=1)
##performing SMOTE
smote=SMOTE(k_neighbors=1)
train_X_smote,train_Y_smote=smote.fit_resample(train_X,train_Y)
#Fitting SVC
svc.fit(train_X_smote,train_Y_smote)
```

Out[115]:
```
SVC
SVC(probability=True, random_state=87)
```

8. Checking the Performance measures for the selected model on the test dataset:

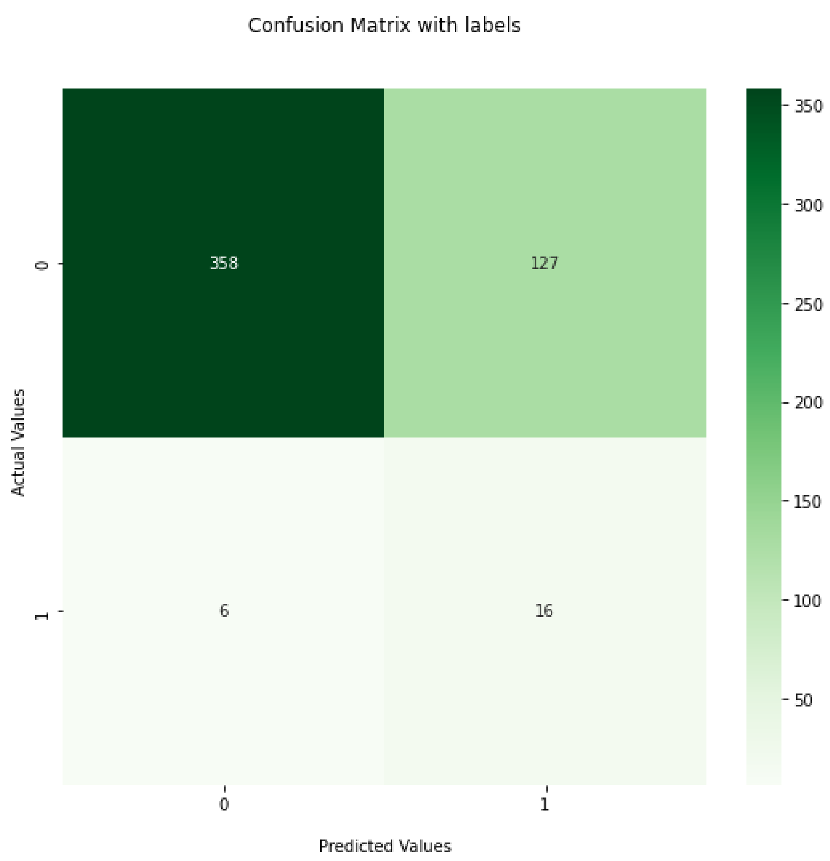
In [116…
```python
# Splitting the test dataset into feature vectors and output vector
testY=test_data['stroke']
testX=test_data.drop(['stroke']+['id'],axis=1)
```

In [117…
```python
# Classification using SVC
svc_pred_test = svc.predict(testX)
```

In [118…
```python
from sklearn.metrics import confusion_matrix, accuracy_score,recall_score, precision_score
cm = confusion_matrix(testY,svc_pred_test)
cm
```

Out[118]:
```
array([[358, 127],
       [  6,  16]], dtype=int64)
```

In [119…
```python
plt.figure(figsize=(9, 8))
cmplot=sns.heatmap(cm, annot = True, fmt = "d",cmap='Greens')
cmplot.set_title('Confusion Matrix with labels\n\n');
cmplot.set_xlabel('\nPredicted Values')
cmplot.set_ylabel('Actual Values ')
plt.show()
```



In [120…
```python
acc= accuracy_score(testY,svc_pred_test)
acc
```

Out[120]:
```
0.73767258382643
```

In [121…
```python
rec=recall_score(testY,svc_pred_test)
rec
```

Out[121]:
```
0.7272727272727273
```

In [122…
```python
precision=precision_score(testY,svc_pred_test)
precision
```

Out[122]:
```
0.11188811188811189
```

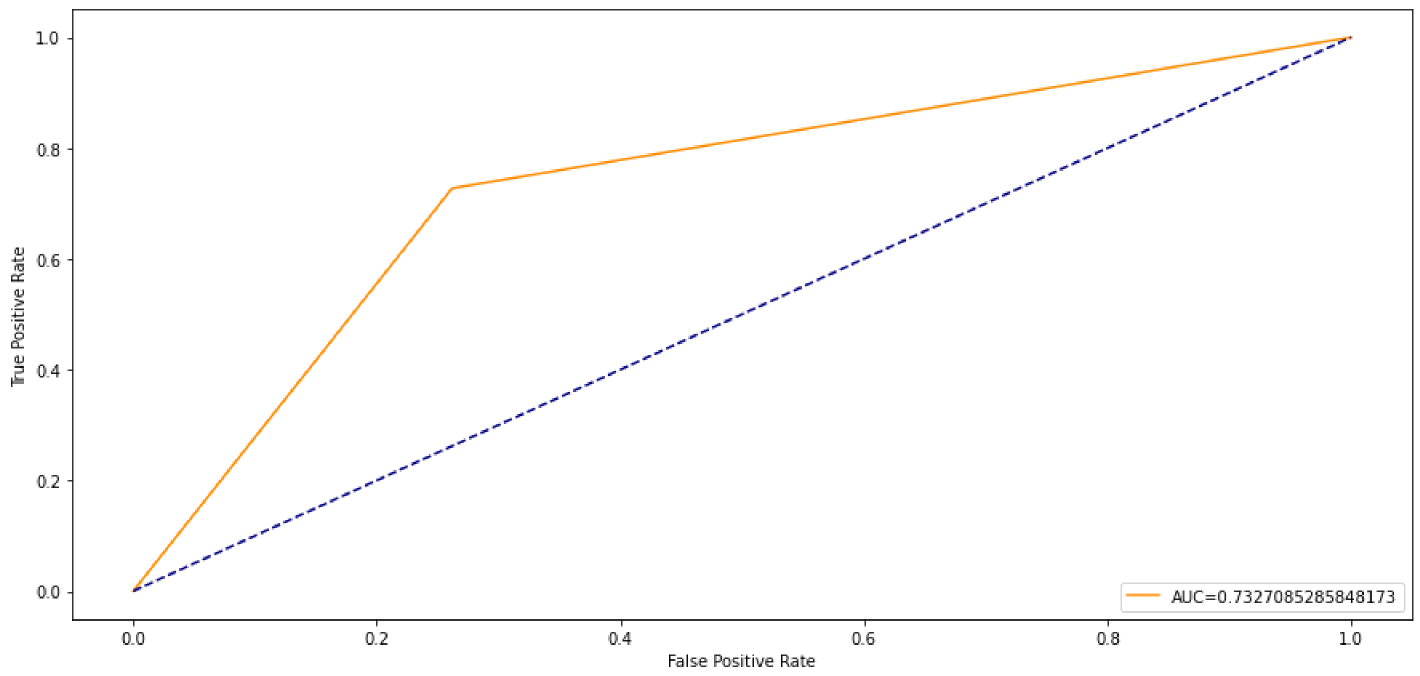
In [123…
```python
sensitivity=cm[1,1]/(cm[1,1]+cm[1,0])
sensitivity
```

Out[123]:
```
0.7272727272727273
```

In [124…
```python
specificity=cm[0,0]/(cm[0,0]+cm[0,1])
specificity
```

Out[124]:
```
0.7381443298969073
```

In [125…
```python
# ROC-AUC for SVC on test data
from sklearn.metrics import roc_curve
fpr, tpr,_ = roc_curve(testY,svc_pred_test)
auc = roc_auc_score(testY,svc_pred_test)
plt.figure(figsize = (15,7))
plt.plot(fpr,tpr,label="AUC="+str(auc),color='darkorange')
plt.plot([0, 1], [0, 1], color="navy", linestyle="--")
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.legend(loc=4)
plt.show()
```



The above permorfance measures on the test data indicate that the model fits the data well enough.

9. Prediction Drift

In [126…
```python
#Splitting the live datasets into feature vectors and output vector
```

```
l1Y=l1['stroke']
l1X=l1.drop(['stroke']+['id'],axis=1)
l2Y=l2['stroke']
l2X=l2.drop(['stroke']+['id'],axis=1)
l3Y=l3['stroke']
l3X=l3.drop(['stroke']+['id'],axis=1)
```

In [127…

```
# Predicted probabilities for the live datasets
svc_prob_l1 = svc.predict_proba(l1X)
svc_prob_l2 = svc.predict_proba(l2X)
svc_prob_l3 = svc.predict_proba(l3X)
# Predicted probabilities for the test dataset
svc_prob_test=svc.predict_proba(testX)
```

In [128…

```
# K-S test for live dataset 1
from scipy.stats import ks_2samp
test_l1_1 = ks_2samp(svc_prob_test[0:507,1],svc_prob_l1[0:511,1])
print(test_l1_1)
```

```
KstestResult(statistic=0.03771851611683013, pvalue=0.8426451588117593)
```

In [129…

```
# K-S test for live dataset 2
test_l2 = ks_2samp(svc_prob_test[0:507,1],svc_prob_l2[0:511,1])
print(test_l2)
```

```
KstestResult(statistic=0.06321672707341833, pvalue=0.2456438132009825)
```

In [130…

```
# K-S test for live dataset 3
test_l3 = ks_2samp(svc_prob_test[0:507,1],svc_prob_l3[0:511,1])
print(test_l3)
```

```
KstestResult(statistic=0.07090556089502349, pvalue=0.1444540155048032)
```

In [131…

```
# K-S test for live dataset 4
l4 = pd.read_csv("C:/Users/rahul/Summer Project/Dataset/Live Dataet 4.csv")
l4Y=l4['stroke']
l4X=l4.drop(['stroke']+['id'],axis=1)
svc_prob_l4 = svc.predict_proba(l4X)
test_l4 = ks_2samp(svc_prob_test[0:507,1],svc_prob_l4[0:299,1])
print(test_l4)
```

```
KstestResult(statistic=0.42792213360775233, pvalue=8.992398632834792e-32)
```

Here we take 5% level of significance.

Observations :

- From the above tests,it is pretty clear that prediction drift has occurred only for the fourth live dataset.
- In the other three live datasets, no prediction drift occurred.

10. Feature Drift

Now we will perform **Kolmogorov-Smirnov test for the continuous variables** and **for categorical variables**, we will use **Chi Square Test**. We will **compare the p values** obtained from the tests mentioned above **with** the corresponding **Benjamini Hochberg FDR values to detect whether there is a drift or not** for a particular feature. The results are shown in a table for each of the live datasets.

In [132…

```
#Storing the coloumn heads for categorical and continuous variables
L1=['age','avg_glucose_level','bmi']
L2=list(train_X_smote.columns)
for i in L1:
    L2.remove(i)
```

10.1 For live dataset 1

In [133…

```
# Test(Kolmogorov-Smirnov or K-S test) for determinig the presence of feature drift in the continuous variables

dict1=dict() #Creating an empty dictionary for storing features and p values

for i in L1:
    test_statistic,pvalue = ks_2samp(train_X_smote[i],l1X[i])
    print(f"\nFor {i} : K-StestResult(statistic={test_statistic},pvalue={pvalue})")
    dict1[i]=pvalue
```

```
For age : K-StestResult(statistic=0.2634388123151296,pvalue=2.82800503051853e-29)

For avg_glucose_level : K-StestResult(statistic=0.10942713781194094,pvalue=2.3492753279064083e-05)

For bmi : K-StestResult(statistic=0.08193649763560744,pvalue=0.0034155056455822397)
```

In [134…

```
# Test(Chi-Squared Test) for determinig the presence of feature drift in the continuous variables
from alibi_detect.cd import ChiSquareDrift
trainX_categoricals=train_X_smote.loc[:, train_X_smote.columns.drop(L1)]
l1_categoricals=l1X.loc[:, l1X.columns.drop(L1)]
for i in L2:
    cd=ChiSquareDrift(trainX_categoricals[i].to_numpy())
    p_value=cd.predict(l1_categoricals[i].to_numpy())
    test_statistic,pvalue =(p_value["data"]["distance"][0],p_value["data"]["p_val"][0])
    print(f"\nFor {i} : ChiSquareTestResult(statistic={test_statistic},pvalue={pvalue})")
    dict1[i]=pvalue
```

```
For hypertension : ChiSquareTestResult(statistic=4.144659996032715,pvalue=0.04176604747772217)

For heart_disease : ChiSquareTestResult(statistic=0.004498933907598257,pvalue=0.9465227127075195)

For gender_Female : ChiSquareTestResult(statistic=36.91356658935547,pvalue=1.2348372324666457e-09)

For gender_Male : ChiSquareTestResult(statistic=16.124479293823242,pvalue=5.931243867962621e-05)

For gender_Other : ChiSquareTestResult(statistic=0.0,pvalue=1.0)

For ever_married_No : ChiSquareTestResult(statistic=48.929786682128906,pvalue=2.6529106602474206e-12)

For ever_married_Yes : ChiSquareTestResult(statistic=3.7446796894073486,pvalue=0.05297587811946869)

For work_type_Govt_job : ChiSquareTestResult(statistic=10.473331451416016,pvalue=0.0012111011892557144)

For work_type_Never_worked : ChiSquareTestResult(statistic=0.0,pvalue=1.0)

For work_type_Private : ChiSquareTestResult(statistic=14.444476127624512,pvalue=0.00014435258344747126)

For work_type_Self-employed : ChiSquareTestResult(statistic=5.415855884552002,pvalue=0.01995466835796833)

For work_type_children : ChiSquareTestResult(statistic=25.000873565673828,pvalue=5.73043223539571e-07)

For Residence_type_Rural : ChiSquareTestResult(statistic=49.116661071777344,pvalue=2.4118311514609303e-12)

For Residence_type_Urban : ChiSquareTestResult(statistic=2.251976490020752,pvalue=0.13344386219978333)

For smoking_status_Unknown : ChiSquareTestResult(statistic=63.518775939941406,pvalue=1.58845613257904e-15)

For smoking_status_formerly smoked : ChiSquareTestResult(statistic=2.667860269546509,pvalue=0.10239360481500626)

For smoking_status_never smoked : ChiSquareTestResult(statistic=22.54230499267578,pvalue=2.0556626623147167e-06)

For smoking_status_smokes : ChiSquareTestResult(statistic=18.50150489807129,pvalue=1.6977026461972855e-05)
```

In [135…

```
# Showing the result of drift detection

dictkey_list1=list(dict1.keys())  # creating a list containing  the dict1 keys
pvalue_list1=list(dict1.values()) # creating a list containing  the dict1 values
pvalue_list1.sort() #sorting the list
rank1_pvalues=list(range(1,22)) # rank list of p values
delta=0.05
BH_FDR_1=[j*(delta/21) for j in rank1_pvalues] # creating a list containing  the Benjamini-Hochberg FDR values
# Creating List of Feature and Drift/Decision
feature_l1=[]
decision_l1=[]
for i in pvalue_list1:
    for j in dictkey_list1:
        if dict1[j]==i:
            feature_l1.append(j)
for i in range(0,21):
    if pvalue_list1[i]<=BH_FDR_1[i]:
        decision_l1.append("Drift")
    else:
         decision_l1.append("No Drift")
del feature_l1[21:23] # nahole besi niye nicchilo dictionary te duto value jegulor p value 1

# Creating DataFrame
dictionary1={"Rank":rank1_pvalues,"Feature":feature_l1,"p-values":pvalue_list1,"BH_FDR":BH_FDR_1,"Decision":decision_l1}
df_l1=pd.DataFrame(dictionary1)
df_l1
```

Out[135]:

	Rank	Feature	p-values	BH_FDR	Decision
0	1	age	2.828005e-29	0.002381	Drift
1	2	smoking_status_Unknown	1.588456e-15	0.004762	Drift
2	3	Residence_type_Rural	2.411831e-12	0.007143	Drift
3	4	ever_married_No	2.652911e-12	0.009524	Drift
4	5	gender_Female	1.234837e-09	0.011905	Drift
5	6	work_type_children	5.730432e-07	0.014286	Drift
6	7	smoking_status_never smoked	2.055663e-06	0.016667	Drift
7	8	smoking_status_smokes	1.697703e-05	0.019048	Drift
8	9	avg_glucose_level	2.349275e-05	0.021429	Drift
9	10	gender_Male	5.931244e-05	0.023810	Drift
10	11	work_type_Private	1.443526e-04	0.026190	Drift
11	12	work_type_Govt_job	1.211101e-03	0.028571	Drift
12	13	bmi	3.415506e-03	0.030952	Drift
13	14	work_type_Self-employed	1.995467e-02	0.033333	Drift
14	15	hypertension	4.176605e-02	0.035714	No Drift
15	16	ever_married_Yes	5.297588e-02	0.038095	No Drift
16	17	smoking_status_formerly smoked	1.023936e-01	0.040476	No Drift
17	18	Residence_type_Urban	1.334439e-01	0.042857	No Drift
18	19	heart_disease	9.465227e-01	0.045238	No Drift
19	20	gender_Other	1.000000e+00	0.047619	No Drift
20	21	work_type_Never_worked	1.000000e+00	0.050000	No Drift

10.2 For live dataset 2

In [136…

```
# Test(Kolmogorov-Smirnov or K-S test) for determinig the presence of feature drift in the continuous variables

dict2=dict() #Creating an empty dictionary for storing features and p values

for i in L1:
    test_statistic,pvalue = ks_2samp(train_X_smote[i],l2X[i])
    print(f"\nFor {i} : K-StestResult(statistic={test_statistic},pvalue={pvalue})")
    dict2[i]=pvalue
```

```
For age : K-StestResult(statistic=0.294742913036439,pvalue=1.1159878644600099e-36)

For avg_glucose_level : K-StestResult(statistic=0.14993318970295114,pvalue=1.1039671399259987e-09)

For bmi : K-StestResult(statistic=0.10646383745716449,pvalue=4.3060250340509754e-05)
```

In [137…

```
# Test(Chi-Squared Test) for determinig the presence of feature drift in the continuous variables
l2_categoricals=l2X.loc[:, l2X.columns.drop(L1)]
for i in L2:
    cd=ChiSquareDrift(trainX_categoricals[i].to_numpy())
    p_value=cd.predict(l2_categoricals[i].to_numpy())
    test_statistic,pvalue =(p_value["data"]["distance"][0],p_value["data"]["p_val"][0])
    print(f"\nFor {i} : ChiSquareTestResult(statistic={test_statistic},pvalue={pvalue})")
    dict2[i]=pvalue
```

```
For hypertension : ChiSquareTestResult(statistic=0.4813259541988373,pvalue=0.4878223240375519)

For heart_disease : ChiSquareTestResult(statistic=0.2682144045829773,pvalue=0.6045320630073547)

For gender_Female : ChiSquareTestResult(statistic=39.00444030761719,pvalue=4.2284259427205484e-10)

For gender_Male : ChiSquareTestResult(statistic=14.014263153076172,pvalue=0.00018142913177143782)

For gender_Other : ChiSquareTestResult(statistic=2.3725955486297607,pvalue=0.12348159402608871)

For ever_married_No : ChiSquareTestResult(statistic=70.9418716430664,pvalue=3.679060474874962e-17)

For ever_married_Yes : ChiSquareTestResult(statistic=10.455445289611816,pvalue=0.0012228841660544276)

For work_type_Govt_job : ChiSquareTestResult(statistic=18.474273681640625,pvalue=1.7221327652805485e-05)

For work_type_Never_worked : ChiSquareTestResult(statistic=0.24629773199558258,pvalue=0.6196941137313843)

For work_type_Private : ChiSquareTestResult(statistic=20.8300838470459,pvalue=5.0188382374471985e-06)

For work_type_Self-employed : ChiSquareTestResult(statistic=2.8946080207824707,pvalue=0.0888763964176178)

For work_type_children : ChiSquareTestResult(statistic=12.046319007873535,pvalue=0.0005189475486986339)

For Residence_type_Rural : ChiSquareTestResult(statistic=44.37766647338867,pvalue=2.7075834629908258e-11)

For Residence_type_Urban : ChiSquareTestResult(statistic=3.39447283744812,pvalue=0.06541527062654495)

For smoking_status_Unknown : ChiSquareTestResult(statistic=47.65448760986328,pvalue=5.083572018199645e-12)

For smoking_status_formerly smoked : ChiSquareTestResult(statistic=3.5163657665252686,pvalue=0.060765553265810001)

For smoking_status_never smoked : ChiSquareTestResult(statistic=39.20815658569336,pvalue=3.8094544185796053e-10)

For smoking_status_smokes : ChiSquareTestResult(statistic=10.185518264770508,pvalue=0.0014154791133478284)
```

In [138…

```
# Showing the result of drift detection

dictkey_list2=list(dict2.keys())  # creating a list containing  the dict1 keys
pvalue_list2=list(dict2.values()) # creating a list containing  the dict1 values
pvalue_list2.sort() #sorting the list
rank2_pvalues=list(range(1,22)) # rank list of p values
delta=0.05
BH_FDR_2=[j*(delta/21) for j in rank2_pvalues] # creating a list containing  the Benjamini-Hochberg FDR values
# Creating list of Feature and Drift/Decision
feature_l2=[]
decision_l2=[]
for i in pvalue_list2:
    for j in dictkey_list2:
        if dict2[j]==i:
            feature_l2.append(j)
for i in range(0,21):
    if pvalue_list2[i]<=BH_FDR_2[i]:
        decision_l2.append("Drift")
    else:
         decision_l2.append("No Drift")

# Creating DataFrame
dictionary2={"Rank":rank2_pvalues,"Feature":feature_l2,"p-values":pvalue_list2,"BH_FDR":BH_FDR_2,"Decision":decision_l2}
df_l2=pd.DataFrame(dictionary2)
df_l2
```

Out[138]:

	Rank	Feature	p-values	BH_FDR	Decision
0	1	age	1.115988e-36	0.002381	Drift
1	2	ever_married_No	3.679060e-17	0.004762	Drift
2	3	smoking_status_Unknown	5.083572e-12	0.007143	Drift
3	4	Residence_type_Rural	2.707583e-11	0.009524	Drift
4	5	smoking_status_never smoked	3.809454e-10	0.011905	Drift
5	6	gender_Female	4.228426e-10	0.014286	Drift
6	7	avg_glucose_level	1.103967e-09	0.016667	Drift
7	8	work_type_Private	5.018838e-06	0.019048	Drift
8	9	work_type_Govt_job	1.722133e-05	0.021429	Drift
9	10	bmi	4.306025e-05	0.023810	Drift
10	11	gender_Male	1.814291e-04	0.026190	Drift
11	12	work_type_children	5.189475e-04	0.028571	Drift
12	13	ever_married_Yes	1.222884e-03	0.030952	Drift
13	14	smoking_status_smokes	1.415479e-03	0.033333	Drift
14	15	smoking_status_formerly smoked	6.076555e-02	0.035714	No Drift
15	16	Residence_type_Urban	6.541527e-02	0.038095	No Drift
16	17	work_type_Self-employed	8.887640e-02	0.040476	No Drift
17	18	gender_Other	1.234816e-01	0.042857	No Drift
18	19	hypertension	4.878223e-01	0.045238	No Drift
19	20	heart_disease	6.045321e-01	0.047619	No Drift
20	21	work_type_Never_worked	6.196941e-01	0.050000	No Drift

10.3 For live dataset 3

In [139…

```
# Test(Kolmogorov-Smirnov or K-S test) for determinig the presence of feature drift in the continuous variables

dict3=dict() #Creating an empty dictionary for storing features and p values

for i in L1:
    test_statistic,pvalue = ks_2samp(train_X_smote[i],l3X[i])
    print(f"\nFor {i} : K-StestResult(statistic={test_statistic},pvalue={pvalue})")
    dict3[i]=pvalue
```

```
For age : K-StestResult(statistic=0.23680001182364233,pvalue=1.1396072275654955e-23)

For avg_glucose_level : K-StestResult(statistic=0.10479173258683155,pvalue=6.0160916429241595e-05)

For bmi : K-StestResult(statistic=0.1054608432541082,pvalue=5.2643288097398155e-05)
```

In [140…

```
# Test(Chi-Squared Test) for determinig the presence of feature drift in the continuous variables
l3_categoricals=l3X.loc[:, l3X.columns.drop(L1)]
for i in L2:
    cd=ChiSquareDrift(trainX_categoricals[i].to_numpy())
    p_value=cd.predict(l3_categoricals[i].to_numpy())
    test_statistic,pvalue =(p_value["data"]["distance"][0],p_value["data"]["p_val"][0])
    print(f"\nFor {i} : ChiSquareTestResult(statistic={test_statistic},pvalue={pvalue})")
    dict3[i]=pvalue
```

```
For hypertension : ChiSquareTestResult(statistic=0.1230868473649025,pvalue=0.725710391998291)

For heart_disease : ChiSquareTestResult(statistic=1.1180850267410278,pvalue=0.2903311848640442)

For gender_Female : ChiSquareTestResult(statistic=15.630699157714844,pvalue=7.699439447605982e-05)

For gender_Male : ChiSquareTestResult(statistic=39.36008834838867,pvalue=3.5242733731344345e-10)

For gender_Other : ChiSquareTestResult(statistic=0.0,pvalue=1.0)

For ever_married_No : ChiSquareTestResult(statistic=61.029327392578125,pvalue=5.623085818588086e-15)

For ever_married_Yes : ChiSquareTestResult(statistic=7.170257568359375,pvalue=0.007412212900817394)

For work_type_Govt_job : ChiSquareTestResult(statistic=11.483617782592773,pvalue=0.0007021232158876956)

For work_type_Never_worked : ChiSquareTestResult(statistic=7.79022216796875,pvalue=0.005252973176538944)

For work_type_Private : ChiSquareTestResult(statistic=10.283634185791016,pvalue=0.0013421535259112716)

For work_type_Self-employed : ChiSquareTestResult(statistic=3.3371288776397705,pvalue=0.06773269921541214)

For work_type_children : ChiSquareTestResult(statistic=34.866886138916016,pvalue=3.5303440171219336e-09)

For Residence_type_Rural : ChiSquareTestResult(statistic=29.666513442993164,pvalue=5.131363423060975e-08)

For Residence_type_Urban : ChiSquareTestResult(statistic=9.227703094482422,pvalue=0.0023838053457438946)

For smoking_status_Unknown : ChiSquareTestResult(statistic=70.46985626220703,pvalue=4.673530425382959e-17)

For smoking_status_formerly smoked : ChiSquareTestResult(statistic=0.087112195789814,pvalue=0.7678810358047485)

For smoking_status_never smoked : ChiSquareTestResult(statistic=21.650142669677734,pvalue=3.2718560305511346e-06)

For smoking_status_smokes : ChiSquareTestResult(statistic=29.150453567504883,pvalue=6.697005972000625e-08)
```

In [141…

```
# Showing the result of drift detection

dictkey_list3=list(dict3.keys())  # creating a list containing  the dict1 keys
pvalue_list3=list(dict3.values()) # creating a list containing  the dict1 values
del pvalue_list3[7] #eleminating the nan element  from the list
pvalue_list3.sort() #sorting the list
rank3_pvalues=list(range(1,21)) # rank list of p values
delta=0.05
BH_FDR_3=[j*(delta/20) for j in rank3_pvalues] # creating a list containing  the Benjamini-Hochberg FDR values
# Creating list of Feature and Drift/Decision
feature_l3=[]
decision_l3=[]
for i in pvalue_list3:
    for j in dictkey_list3:
        if dict3[j]==i:
            feature_l3.append(j)
for i in range(0,20):
    if pvalue_list3[i]<=BH_FDR_3[i]:
        decision_l3.append("Drift")
    else:
         decision_l3.append("No Drift")

# Creating DataFrame
dictionary3={"Rank":rank3_pvalues,"Feature":feature_l3,"p-values":pvalue_list3,"BH_FDR":BH_FDR_3,"Decision":decision_l3}
df_l3=pd.DataFrame(dictionary3)
df_l3
```

Out[141]:

	Rank	Feature	p-values	BH_FDR	Decision
0	1	age	1.139607e-23	0.0025	Drift
1	2	smoking_status_Unknown	4.673530e-17	0.0050	Drift
2	3	ever_married_No	5.623086e-15	0.0075	Drift
3	4	gender_Male	3.524273e-10	0.0100	Drift
4	5	work_type_children	3.530344e-09	0.0125	Drift
5	6	Residence_type_Rural	5.131363e-08	0.0150	Drift
6	7	smoking_status_smokes	6.697006e-08	0.0175	Drift
7	8	smoking_status_never smoked	3.271856e-06	0.0200	Drift
8	9	bmi	5.264329e-05	0.0225	Drift
9	10	avg_glucose_level	6.016092e-05	0.0250	Drift
10	11	gender_Female	7.699439e-05	0.0275	Drift
11	12	work_type_Govt_job	7.021232e-04	0.0300	Drift
12	13	work_type_Private	1.342154e-03	0.0325	Drift
13	14	Residence_type_Urban	2.383805e-03	0.0350	Drift
14	15	work_type_Never_worked	5.252973e-03	0.0375	Drift
15	16	ever_married_Yes	7.412213e-03	0.0400	Drift
16	17	work_type_Self-employed	6.773270e-02	0.0425	No Drift
17	18	heart_disease	2.903312e-01	0.0450	No Drift
18	19	hypertension	7.257104e-01	0.0475	No Drift
19	20	smoking_status_formerly smoked	7.678810e-01	0.0500	No Drift

10.4 For live dataset 4

In [142…

```python
# Test(Kolmogorov-Smirnov or K-S test) for determinig the presence of feature drift in the continuous variables

dict4=dict() #Creating an empty dictionary for storing features and p values

for i in L1:
    test_statistic,pvalue = ks_2samp(train_X_smote[i],l4X[i])
    print(f"\nFor {i} : K-StestResult(statistic={test_statistic},pvalue={pvalue})")
    dict4[i]=pvalue
```

```
For age : K-StestResult(statistic=0.17153413311564925,pvalue=8.703622544903311e-08)

For avg_glucose_level : K-StestResult(statistic=0.0700802652622829,pvalue=0.11645463894621932)

For bmi : K-StestResult(statistic=0.07371637004915113,pvalue=0.0862478409189148)
```

In [143…

```python
# Test(Chi-Squared Test) for determinig the presence of feature drift in the continuous variables
l4_categoricals=l4X.loc[:, l4X.columns.drop(L1)]
for i in L2:
    cd=ChiSquareDrift(trainX_categoricals[i].to_numpy())
    p_value=cd.predict(l4_categoricals[i].to_numpy())
    test_statistic,pvalue =(p_value["data"]["distance"][0],p_value["data"]["p_val"][0])
    print(f"\nFor {i} : ChiSquareTestResult(statistic={test_statistic},pvalue={pvalue})")
    dict4[i]=pvalue
```

```
For hypertension : ChiSquareTestResult(statistic=72.35399627685547,pvalue=1.7985813229575333e-17)

For heart_disease : ChiSquareTestResult(statistic=74.96975708007812,pvalue=4.779792445695297e-18)

For gender_Female : ChiSquareTestResult(statistic=16.030824661254883,pvalue=6.231955194380134e-05)

For gender_Male : ChiSquareTestResult(statistic=14.890359878540039,pvalue=0.00011394375906093046)

For gender_Other : ChiSquareTestResult(statistic=0.0,pvalue=1.0)

For ever_married_No : ChiSquareTestResult(statistic=2.350435495376587,pvalue=0.1252480149269104)

For ever_married_Yes : ChiSquareTestResult(statistic=22.53072166442871,pvalue=2.0680952275142772e-06)

For work_type_Govt_job : ChiSquareTestResult(statistic=6.5391058921813965,pvalue=0.010552837513387203)

For work_type_Never_worked : ChiSquareTestResult(statistic=0.013236531987786293,pvalue=0.9084053635597229)

For work_type_Private : ChiSquareTestResult(statistic=16.474388122558594,pvalue=4.931171497446485e-05)

For work_type_Self-employed : ChiSquareTestResult(statistic=29.120899200439453,pvalue=6.799949403557548e-08)

For work_type_children : ChiSquareTestResult(statistic=6.704691410064697,pvalue=0.009615955874323845)

For Residence_type_Rural : ChiSquareTestResult(statistic=9.34696102142334,pvalue=0.0022335557732731104)

For Residence_type_Urban : ChiSquareTestResult(statistic=12.117152214050293,pvalue=0.0004996013594791293)

For smoking_status_Unknown : ChiSquareTestResult(statistic=3.8221354484558105,pvalue=0.0505797378718853)

For smoking_status_formerly smoked : ChiSquareTestResult(statistic=26.219451904296875,pvalue=3.047374264042446e-07)

For smoking_status_never smoked : ChiSquareTestResult(statistic=17.468238830566406,pvalue=2.9214790629339404e-05)

For smoking_status_smokes : ChiSquareTestResult(statistic=12.661612510681152,pvalue=0.00037324015283957124)
```

In [144…

```python
# Showing the result of drift detection

dictkey_list4=list(dict4.keys())  # creating a list containing  the dict1 keys
pvalue_list4=list(dict4.values()) # creating a list containing  the dict1 values
del pvalue_list4[7] #eleminating the nan element  from the list
pvalue_list4.sort() #sorting the list
rank4_pvalues=list(range(1,21)) # rank list of p values
delta=0.05
BH_FDR_4=[j*(delta/20) for j in rank4_pvalues] # creating a list containing  the Benjamini-Hochberg FDR values
# Creating list of Feature and Drift/Decision
feature_l4=[]
decision_l4=[]
for i in pvalue_list4:
    for j in dictkey_list4:
        if dict4[j]==i:
            feature_l4.append(j)
for i in range(0,20):
    if pvalue_list4[i]<=BH_FDR_4[i]:
        decision_l4.append("Drift")
    else:
         decision_l4.append("No Drift")

# Creating DataFrame
dictionary4={"Rank":rank4_pvalues,"Feature":feature_l4,"p-values":pvalue_list4,"BH_FDR":BH_FDR_4,"Decision":decision_l4}
df_l4=pd.DataFrame(dictionary4)
df_l4
```

Out[144]:

	Rank	Feature	p-values	BH_FDR	Decision
0	1	heart_disease	4.779792e-18	0.0025	Drift
1	2	hypertension	1.798581e-17	0.0050	Drift
2	3	work_type_Self-employed	6.799949e-08	0.0075	Drift
3	4	age	8.703623e-08	0.0100	Drift
4	5	smoking_status_formerly smoked	3.047374e-07	0.0125	Drift
5	6	ever_married_Yes	2.068095e-06	0.0150	Drift
6	7	smoking_status_never smoked	2.921479e-05	0.0175	Drift
7	8	work_type_Private	4.931171e-05	0.0200	Drift
8	9	gender_Female	6.231955e-05	0.0225	Drift
9	10	gender_Male	1.139438e-04	0.0250	Drift
10	11	smoking_status_smokes	3.732402e-04	0.0275	Drift
11	12	Residence_type_Urban	4.996014e-04	0.0300	Drift
12	13	Residence_type_Rural	2.233556e-03	0.0325	Drift
13	14	work_type_children	9.615956e-03	0.0350	Drift
14	15	work_type_Govt_job	1.055284e-02	0.0375	Drift
15	16	smoking_status_Unknown	5.057974e-02	0.0400	No Drift
16	17	bmi	8.624784e-02	0.0425	No Drift
17	18	avg_glucose_level	1.164546e-01	0.0450	No Drift
18	19	ever_married_No	1.252480e-01	0.0475	No Drift
19	20	work_type_Never_worked	9.084054e-01	0.0500	No Drift