In [1]:
```
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
import numpy as np
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from matplotlib import pyplot as plt
%matplotlib inline
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import mutual_info_classif
from sklearn.model_selection import cross_val_score
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix

### Importing all the libraries for the ananlysis
```

In [2]:
```
train_data = pd.read_csv('healthcare-dataset-stroke-data.csv') # importing datase
```

In [3]:
```
train_data.columns
```

Out[3]:
```
Index(['id', 'gender', 'age', 'hypertension', 'heart_disease', 'ever_married',
       'work_type', 'Residence_type', 'avg_glucose_level', 'bmi',
       'smoking_status', 'stroke'],
      dtype='object')
```

In [4]:
```
train_data.dtypes       #checking datatype for columns in the dataset
```

Out[4]:
```
id                     int64
gender                object
age                  float64
hypertension           int64
heart_disease          int64
ever_married          object
work_type             object
Residence_type        object
avg_glucose_level    float64
bmi                  float64
smoking_status        object
stroke                 int64
dtype: object
```

In [5]:
```
train_data.isnull().sum()     #checking if we have any null values in the dataset
```

Out[5]:
```
id                     0
gender                 0
age                    0
hypertension           0
heart_disease          0
ever_married           0
work_type              0
Residence_type         0
avg_glucose_level      0
bmi                  201
smoking_status         0
stroke                 0
dtype: int64
```

In [6]:
```
train_data
```

Out[6]:

	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
...	...	...	...	...	...	...	...	...
5105	18234	Female	80.0	1	0	Yes	Private	Urban
5106	44873	Female	81.0	0	0	Yes	Self-employed	Urban
5107	19723	Female	35.0	0	0	Yes	Self-employed	Rural
5108	37544	Male	51.0	0	0	Yes	Private	Rural
5109	44679	Female	44.0	0	0	Yes	Govt_job	Urban

5110 rows × 12 columns

In [7]:
```
train_data['stroke'].value_counts(normalize=True)     #counting the value of stro
```

Out[7]:
```
0    0.951272
1    0.048728
Name: stroke, dtype: float64
```

In [8]:
```
train_data['bmi'].round()  #Rounding the values of Bmi column so that we can conv
```

Out[8]:
```
0       37.0
1        NaN
2       32.0
3       34.0
4       24.0
        ... 
5105     NaN
5106    40.0
5107    31.0
5108    26.0
5109    26.0
Name: bmi, Length: 5110, dtype: float64
```

In [9]:
```
train_data.describe()  # this shows the mathematical ground for each feature
```

Out[9]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	
count	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	4909.000000	51
mean	36517.829354	43.226614	0.097456	0.054012	106.147677	28.893237	
std	21161.721625	22.612647	0.296607	0.226063	45.283560	7.854067	
min	67.000000	0.080000	0.000000	0.000000	55.120000	10.300000	
25%	17741.250000	25.000000	0.000000	0.000000	77.245000	23.500000	
50%	36932.000000	45.000000	0.000000	0.000000	91.885000	28.100000	
75%	54682.000000	61.000000	0.000000	0.000000	114.090000	33.100000	
max	72940.000000	82.000000	1.000000	1.000000	271.740000	97.600000	

Checking for Null values

Manipulating the null value

In [10]:
```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5110 entries, 0 to 5109
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 5110 non-null   int64  
 1   gender             5110 non-null   object 
 2   age                5110 non-null   float64
 3   hypertension       5110 non-null   int64  
 4   heart_disease      5110 non-null   int64  
 5   ever_married       5110 non-null   object 
 6   work_type          5110 non-null   object 
 7   Residence_type     5110 non-null   object 
 8   avg_glucose_level  5110 non-null   float64
 9   bmi                4909 non-null   float64
 10  smoking_status     5110 non-null   object 
 11  stroke             5110 non-null   int64  
dtypes: float64(3), int64(4), object(5)
memory usage: 479.2+ KB
```

In [11]:
```
train_data.isnull().sum()     # checking total number of null values in the datas
```

Out[11]:
```
id                     0
gender                 0
age                    0
hypertension           0
heart_disease          0
ever_married           0
work_type              0
Residence_type         0
avg_glucose_level      0
bmi                  201
smoking_status         0
stroke                 0
dtype: int64
```

In [12]:
```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5110 entries, 0 to 5109
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 5110 non-null   int64  
 1   gender             5110 non-null   object 
 2   age                5110 non-null   float64
 3   hypertension       5110 non-null   int64  
 4   heart_disease      5110 non-null   int64  
 5   ever_married       5110 non-null   object 
 6   work_type          5110 non-null   object 
 7   Residence_type     5110 non-null   object 
 8   avg_glucose_level  5110 non-null   float64
 9   bmi                4909 non-null   float64
 10  smoking_status     5110 non-null   object 
 11  stroke             5110 non-null   int64  
dtypes: float64(3), int64(4), object(5)
memory usage: 479.2+ KB
```

In [13]:
```
#Changing Bmi null value to mean values of Bmi as for health purpose Average Bmi
train_data['bmi'] = train_data['bmi'].fillna(train_data['bmi'].mean())
```

In [14]:
```
train_data
```

Out[14]:

	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
...	...	...	...	...	...	...	...	...
5105	18234	Female	80.0	1	0	Yes	Private	Urban
5106	44873	Female	81.0	0	0	Yes	Self-employed	Urban
5107	19723	Female	35.0	0	0	Yes	Self-employed	Rural
5108	37544	Male	51.0	0	0	Yes	Private	Rural
5109	44679	Female	44.0	0	0	Yes	Govt_job	Urban

5110 rows × 12 columns

In [15]:
```
train_data.isnull().sum()
```

Out[15]:
```
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
```

In [16]:
```
train_data.describe() #after changing the null values we can see there was a diff
```

Out[16]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	
count	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	51
mean	36517.829354	43.226614	0.097456	0.054012	106.147677	28.893237	
std	21161.721625	22.612647	0.296607	0.226063	45.283560	7.698018	
min	67.000000	0.080000	0.000000	0.000000	55.120000	10.300000	
25%	17741.250000	25.000000	0.000000	0.000000	77.245000	23.800000	
50%	36932.000000	45.000000	0.000000	0.000000	91.885000	28.400000	
75%	54682.000000	61.000000	0.000000	0.000000	114.090000	32.800000	
max	72940.000000	82.000000	1.000000	1.000000	271.740000	97.600000	

In [17]:
```
train_data['bmi'] = train_data['bmi'].round()
#Bmi = train_data['bmi'].astype(int)
```

In [18]:
```
train_data['bmi']
```

Out[18]:
```
0       37.0
1       29.0
2       32.0
3       34.0
4       24.0
        ...
5105    29.0
5106    40.0
5107    31.0
5108    26.0
5109    26.0
Name: bmi, Length: 5110, dtype: float64
```

In [19]:
```
Bmi = train_data['bmi']
```

In [20]:
```
Bmi
```

Out[20]:
```
0       37.0
1       29.0
2       32.0
3       34.0
4       24.0
        ...
5105    29.0
5106    40.0
5107    31.0
5108    26.0
5109    26.0
Name: bmi, Length: 5110, dtype: float64
```

In [21]:
```
train_data['stroke'].value_counts()
```

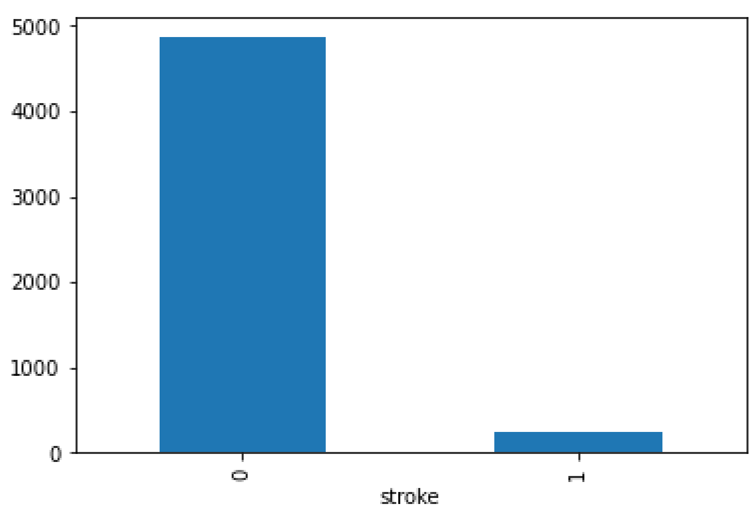
Out[21]:
```
0    4861
1     249
Name: stroke, dtype: int64
```

In [22]:
```
train_data['stroke'].value_counts(normalize=True)
```

Out[22]:
```
0    0.951272
1    0.048728
Name: stroke, dtype: float64
```

In [23]:
```
train_data['stroke'].value_counts().plot.bar(xlabel='stroke')  #Plotting bar to c
```

Out[23]:
```
<AxesSubplot:xlabel='stroke'>
```

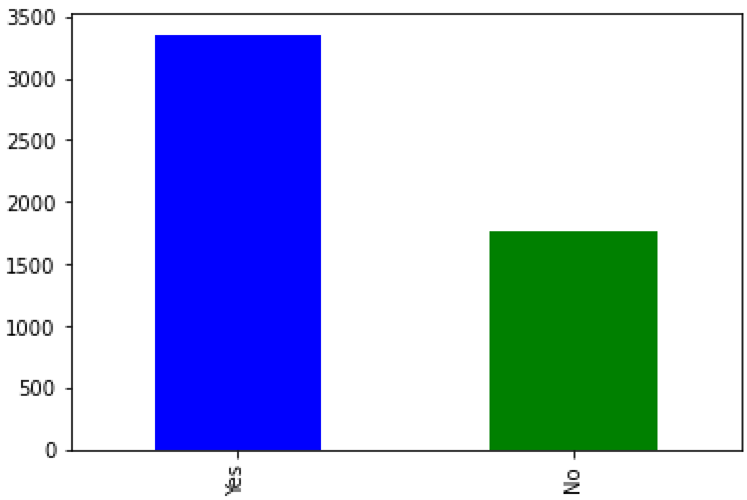


In [24]:
```
train_data['ever_married'].value_counts()
```

Out[24]:
```
Yes    3353
No     1757
Name: ever_married, dtype: int64
```

In [25]:
```
train_data['ever_married'].value_counts().plot(kind='bar', color=['b','g'])  #sir
```

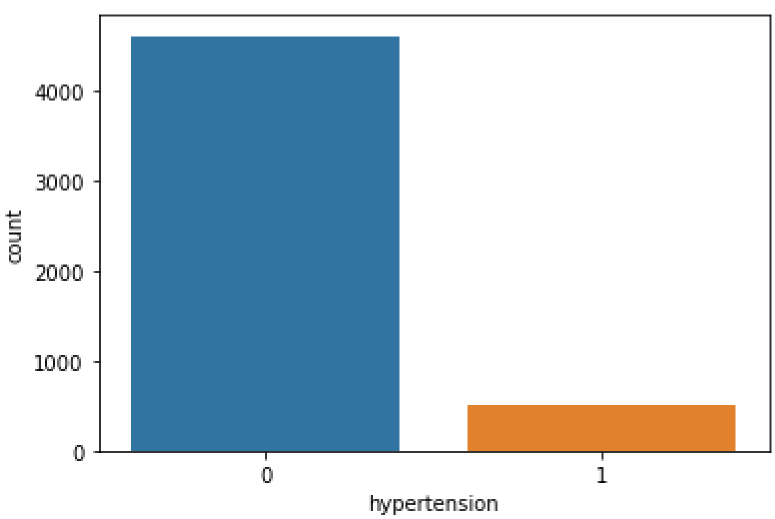
Out[25]: <AxesSubplot:>



Plotting and Analysis using seaborn

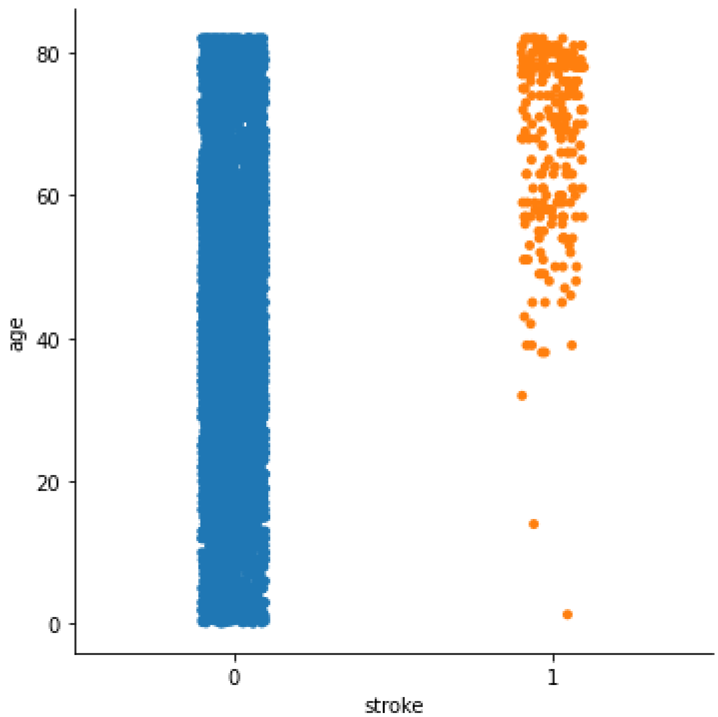
In [26]:
```
sns.countplot(train_data['hypertension'])   #here we check the number of people w
```

Out[26]: <AxesSubplot:xlabel='hypertension', ylabel='count'>



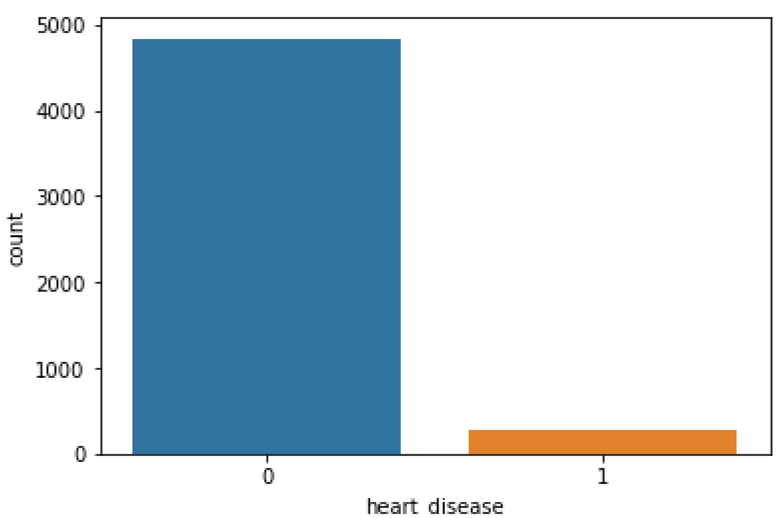
In [27]:
```
sns.catplot(x='stroke',y='age', data=train_data)    #This graph shows number strok
```

Out[27]: <seaborn.axisgrid.FacetGrid at 0x24d0e640400>



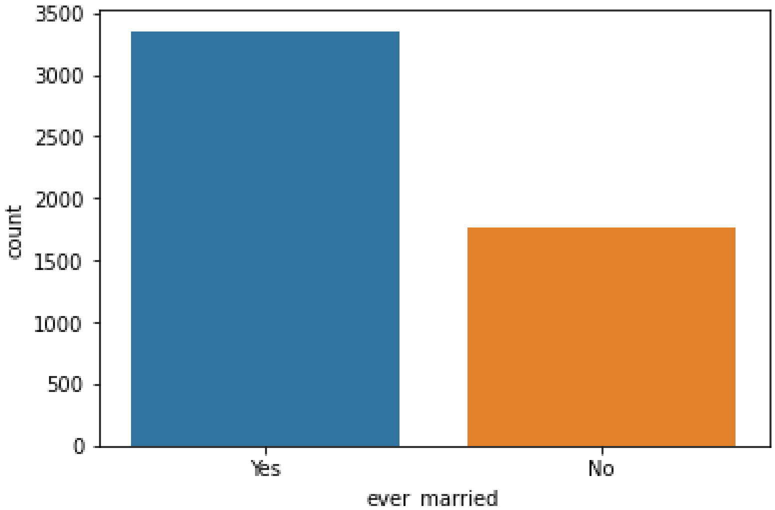
In [28]:
```
sns.countplot(train_data['heart_disease'])
```

Out[28]: <AxesSubplot:xlabel='heart_disease', ylabel='count'>



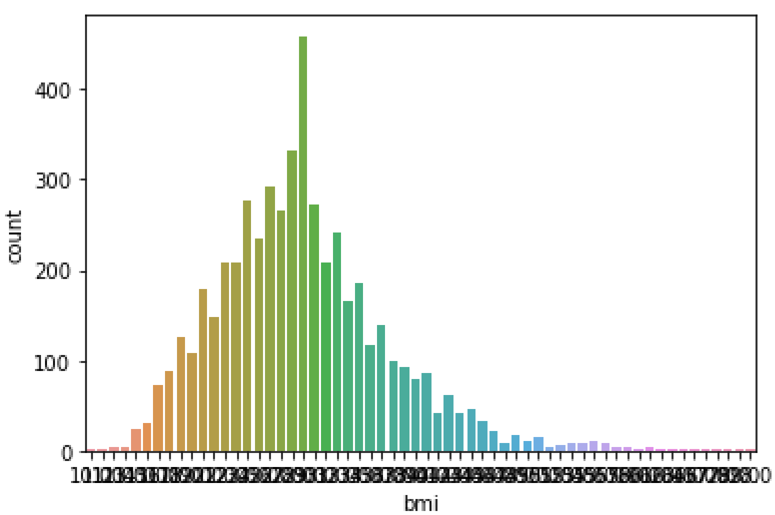
In [29]:
```
sns.countplot(train_data['ever_married'])
```

Out[29]: <AxesSubplot:xlabel='ever_married', ylabel='count'>



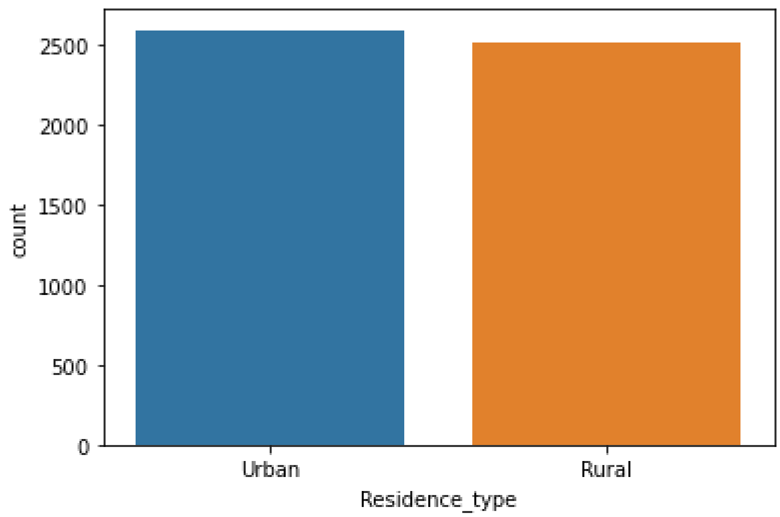
In [30]:
```
sns.countplot(train_data['bmi']) #Numerical Variable of bmi is higher for most o
```

Out[30]: <AxesSubplot:xlabel='bmi', ylabel='count'>



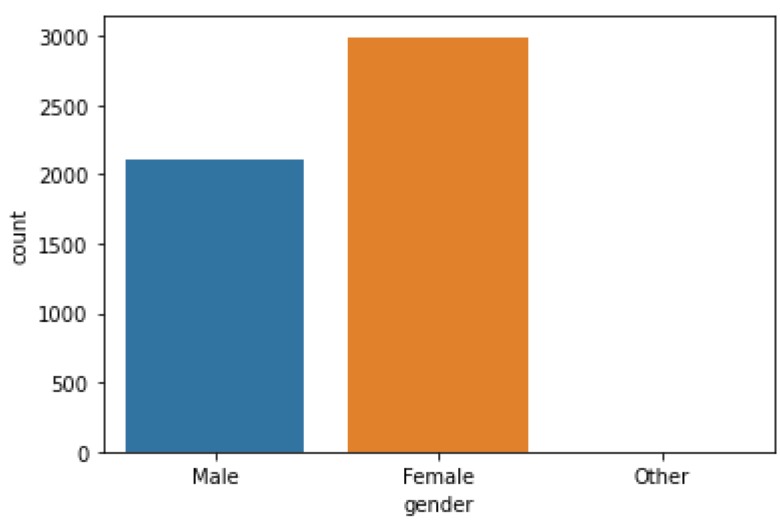
In [31]:
```
sns.countplot(train_data['Residence_type']) #This graph shows there are equal num
```

Out[31]:
```
<AxesSubplot:xlabel='Residence_type', ylabel='count'>
```



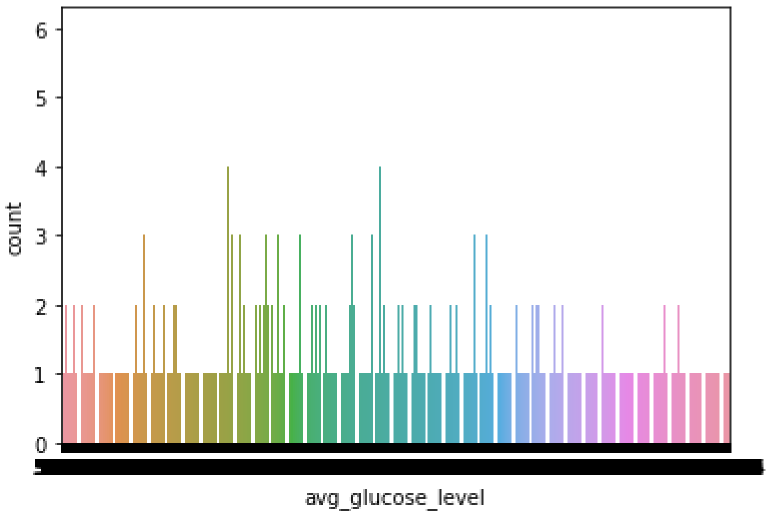
In [32]:
```
sns.countplot(train_data['gender'])   #this graph the dataset is more bended towa
```

Out[32]:
```
<AxesSubplot:xlabel='gender', ylabel='count'>
```



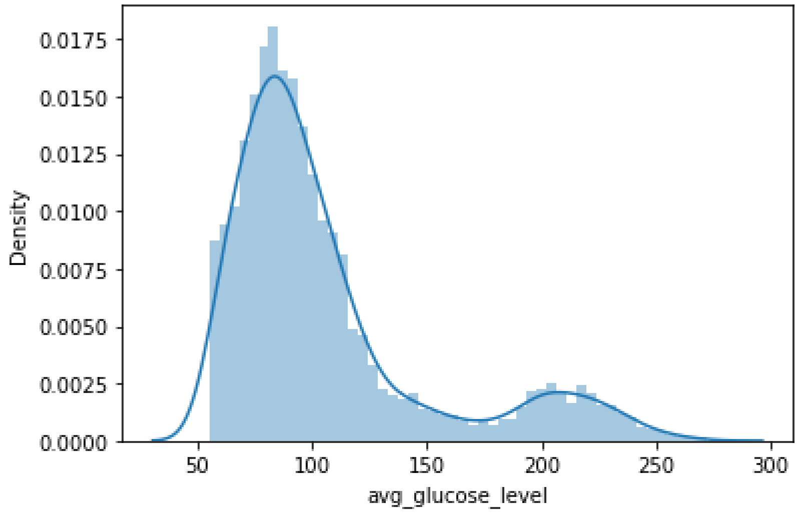
In [33]:
```
sns.countplot(train_data['avg_glucose_level'])  #Numerical variable  showing gluc
```

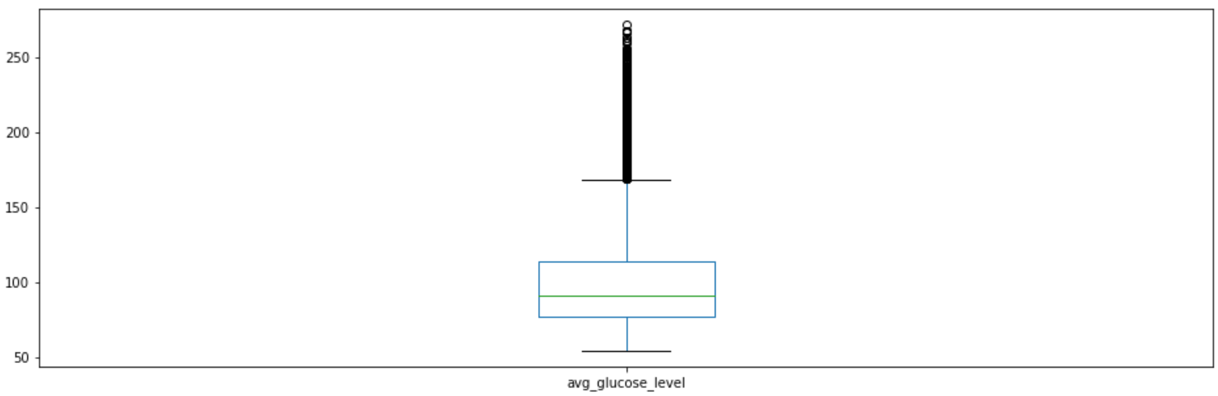
Out[33]:
```
<AxesSubplot:xlabel='avg_glucose_level', ylabel='count'>
```



Independent Variable

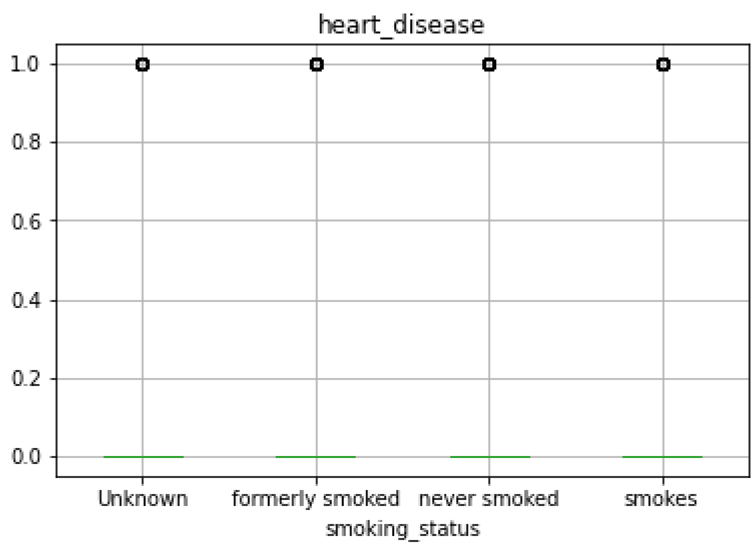
In [34]:
```
sns.distplot(train_data['avg_glucose_level']) #Glucose level can impact on the ou
plt.show()
train_data['avg_glucose_level'].plot.box(figsize=(16,5))
plt.show()
```





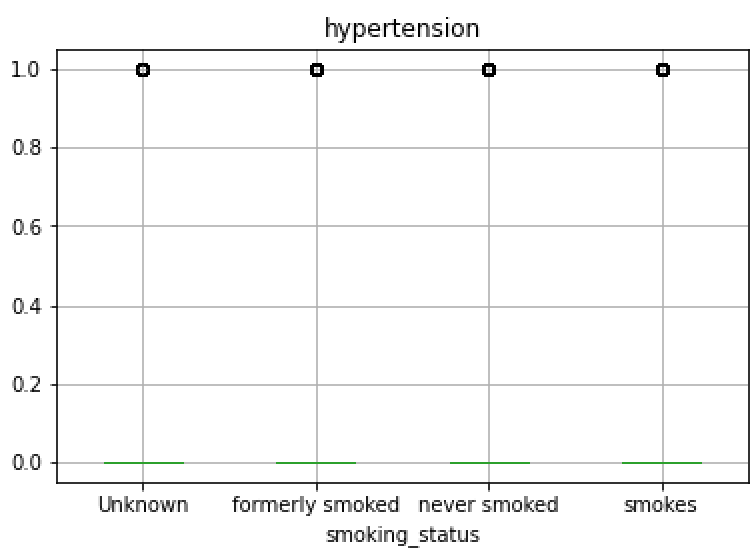
In [35]:
```
lot(column='heart_disease', by = 'smoking_status')  #comparing the boxplot in terr
)
```

Out[35]: Text(0.5, 0.98, '')



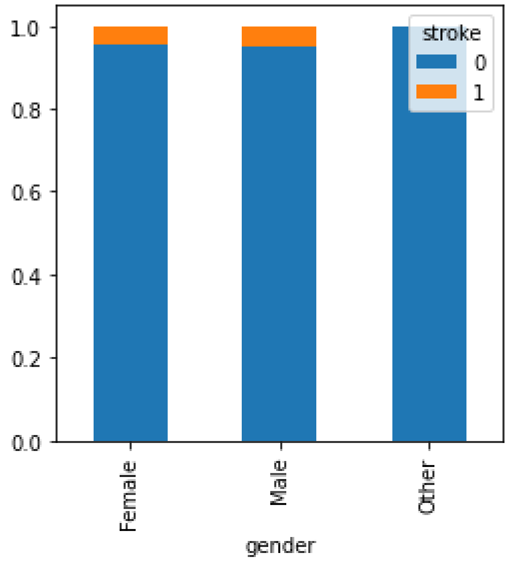
In [36]:
```
train_data.boxplot(column='hypertension', by = 'smoking_status')
plt.suptitle("")
```

Out[36]: Text(0.5, 0.98, '')

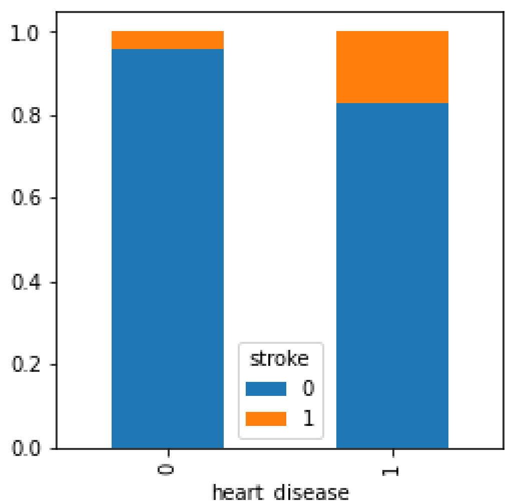


Bivariate Analysis

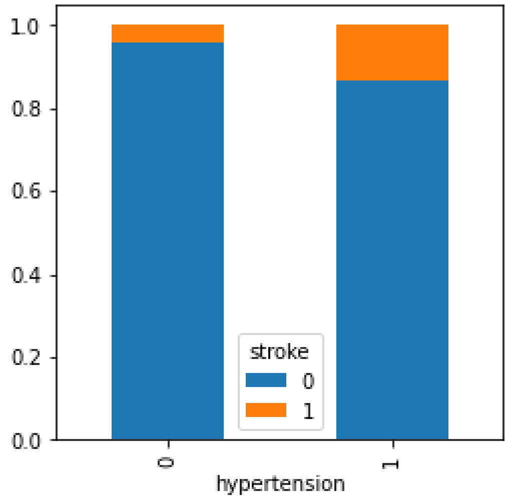
In [37]:
```
Gender=pd.crosstab(train_data['gender'],train_data['stroke']) # Doing bivariate a
Gender.div(Gender.sum(1).astype(float), axis=0).plot(kind="bar",stacked=True,figs
plt.show()
```



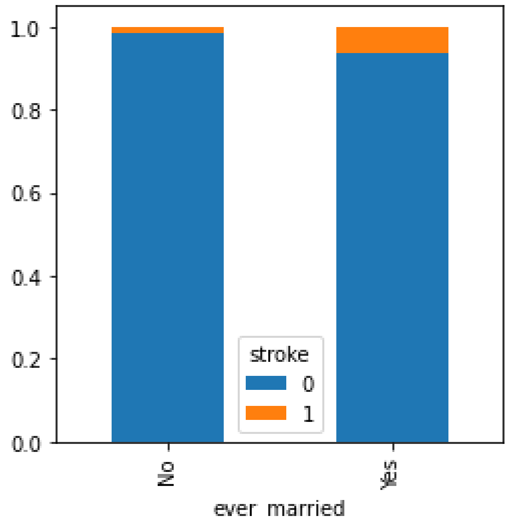
In [38]:
```
heart=pd.crosstab(train_data['heart_disease'],train_data['stroke']) # Doing bivar
heart.div(heart.sum(1).astype(float), axis=0).plot(kind="bar",stacked=True,figsiz
plt.show()
```

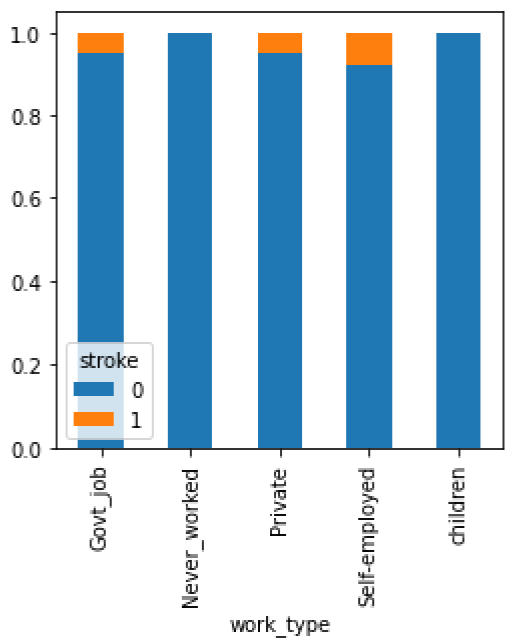


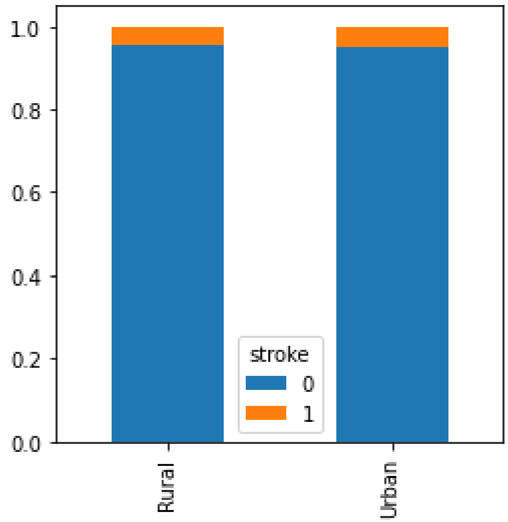
In [39]:
```
b(train_data['hypertension'],train_data['stroke']) # Doing bivariate analysis wit
um(1).astype(float), axis=0).plot(kind="bar",stacked=True,figsize=(4,4))
```



In [40]:
```
#this is a Bivariate graph for remaining dependent features
Married=pd.crosstab(train_data['ever_married'],train_data['stroke'])
Working=pd.crosstab(train_data['work_type'],train_data['stroke'])
Residence=pd.crosstab(train_data['Residence_type'],train_data['stroke'])
Married.div(Married.sum(1).astype(float), axis=0).plot(kind="bar",stacked=True,fi
plt.show()
Working.div(Working.sum(1).astype(float), axis=0).plot(kind="bar",stacked=True,fi
plt.show()
Residence.div(Residence.sum(1).astype(float), axis=0).plot(kind="bar",stacked=Tru
plt.show()
```







One Hot Encoding

In [41]:
```
Work_type = pd.get_dummies(train_data['work_type'])      # Separating the variabl
Residence_area = pd.get_dummies(train_data['Residence_type'])
Smoking_status = pd.get_dummies(train_data['smoking_status'])
Gender = pd.get_dummies(train_data['gender'])
Married = pd.get_dummies(train_data['ever_married'])
```

In [42]:
```
Work_type
```

Out[42]:

	Govt_job	Never_worked	Private	Self-employed	children
0	0	0	1	0	0
1	0	0	0	1	0
2	0	0	1	0	0
3	0	0	1	0	0
4	0	0	0	1	0
...	...	...	...	...	...
5105	0	0	1	0	0
5106	0	0	0	1	0
5107	0	0	0	1	0
5108	0	0	1	0	0
5109	1	0	0	0	0

5110 rows × 5 columns

In [43]:
```
Residence_area
```

Out[43]:

	Rural	Urban
0	0	1
1	1	0
2	1	0
3	0	1
4	1	0
...	...	...
5105	0	1
5106	0	1
5107	1	0
5108	1	0
5109	0	1

5110 rows × 2 columns

In [44]:
```
Smoking_status
```

Out[44]:

	Unknown	formerly smoked	never smoked	smokes
0	0	1	0	0
1	0	0	1	0
2	0	0	1	0
3	0	0	0	1
4	0	0	1	0
...	...	...	...	...
5105	0	0	1	0
5106	0	0	1	0
5107	0	0	1	0
5108	0	1	0	0
5109	1	0	0	0

5110 rows × 4 columns

In [45]:
```
Married
```

Out[45]:

	No	Yes
0	0	1
1	0	1
2	0	1
3	0	1
4	0	1
...	...	...
5105	0	1
5106	0	1
5107	0	1
5108	0	1
5109	0	1

5110 rows × 2 columns

In [46]:
```
Gender
```

Out[46]:

	Female	Male	Other
0	0	1	0
1	1	0	0
2	0	1	0
3	1	0	0
4	1	0	0
...	...	...	...
5105	1	0	0
5106	1	0	0
5107	1	0	0
5108	0	1	0
5109	1	0	0

5110 rows × 3 columns

Making New Variable seperate from Dataset

Making new dataset for every column so that we can't interfere with the main dataset

In [47]:
```
Id = train_data['id']
```

In [48]:
```
Hypertension = train_data['hypertension']
```

In [49]:
```
Heart_disease = train_data['heart_disease']
```

In [50]:
```
Age = train_data['age']
```

In [51]:
```
Avg_glucose_level = train_data['avg_glucose_level']
```

In [52]:
```
train_data.head()
```

Out[52]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	av
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 [53]:
```
Stroke = train_data['stroke']
```

In [54]:
```
train_data['age'].value_counts()
```

Out[54]:
```
78.00    102
57.00     95
52.00     90
54.00     87
51.00     86
        ... 
0.48       3
1.40       3
0.16       3
0.08       2
0.40       2
Name: age, Length: 104, dtype: int64
```

In [55]:
```
train_data['work_type'].value_counts()
```

Out[55]:
```
Private          2925
Self-employed     819
children          687
Govt_job          657
Never_worked       22
Name: work_type, dtype: int64
```

In [56]:
```
train_data['Residence_type'].value_counts()
```

Out[56]:
```
Urban    2596
Rural    2514
Name: Residence_type, dtype: int64
```

In [57]:
```
train_data['avg_glucose_level'].value_counts()
```

Out[57]:
```
93.88     6
72.49     5
84.10     5
91.68     5
83.16     5
         ..
95.02     1
120.09    1
197.58    1
99.91     1
60.50     1
Name: avg_glucose_level, Length: 3979, dtype: int64
```

In [58]:
```
train_data['smoking_status'].value_counts()
```

Out[58]:
```
never smoked       1892
Unknown            1544
formerly smoked     885
smokes              789
Name: smoking_status, dtype: int64
```

In [59]:
```
Stroke.value_counts()
```

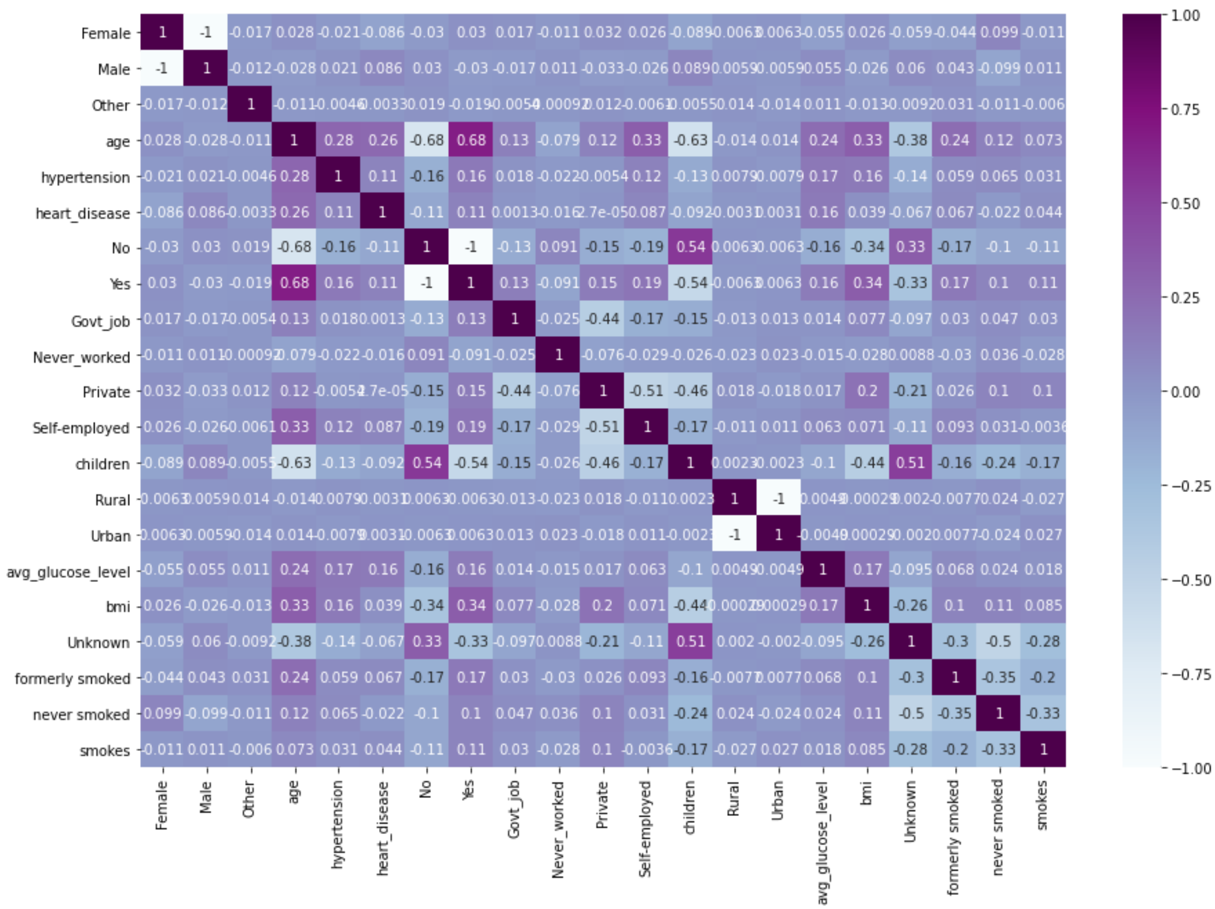
Out[59]:
```
0    4861
1     249
Name: stroke, dtype: int64
```

In [60]:
```
finaldata = pd.concat([Gender, Age, Hypertension, Heart_disease, Married, Work_ty
X = finaldata.iloc[:,0:-1] # concatenating the newly created and manipulated colu
```

Correlation Matrix

In [61]:
```
# this shows the important feature required for the analysis as we can see every
corr=X.corr()
plt.figure(figsize=(15,10))
sns.heatmap(corr, annot = True, cmap="BuPu")  # visualising the correlation matri
```

Out[61]: <AxesSubplot:>



In [62]:
```
y = finaldata['stroke']
```

In [63]:
```
kbest = SelectKBest(score_func = chi2, k = 'all') # target number of features is
ordered_features = kbest.fit(X,y)
```

In [64]:
```
train_data_scores = pd.DataFrame(ordered_features.scores_, columns=['Score']) # s
```

In [65]:
```
train_data_columns = pd.DataFrame(X.columns, columns = ['Feature_name']) # save t
```

In [66]:
```
feature_rank = pd.concat([train_data_scores,train_data_columns],axis=1) # combine
```

In [67]:
```
feature_rank.nlargest(12,'Score') # rank the features by score - the scores are b
```

Out[67]:

	Score	Feature_name
3	3635.226911	age
15	1718.285446	avg_glucose_level
5	87.987436	heart_disease
4	75.449498	hypertension
6	39.355836	No
12	31.111620	children
7	20.622787	Yes
18	17.607359	formerly smoked
11	16.584252	Self-employed
16	15.879229	bmi
17	11.139767	Unknown
9	1.126929	Never_worked

Extra Trees Classifier

In [68]:
```
# initialise the method

model = ExtraTreesClassifier()
model.fit(X,y) # pass the input and output data to the method
```

Out[68]:
```
ExtraTreesClassifier()
```

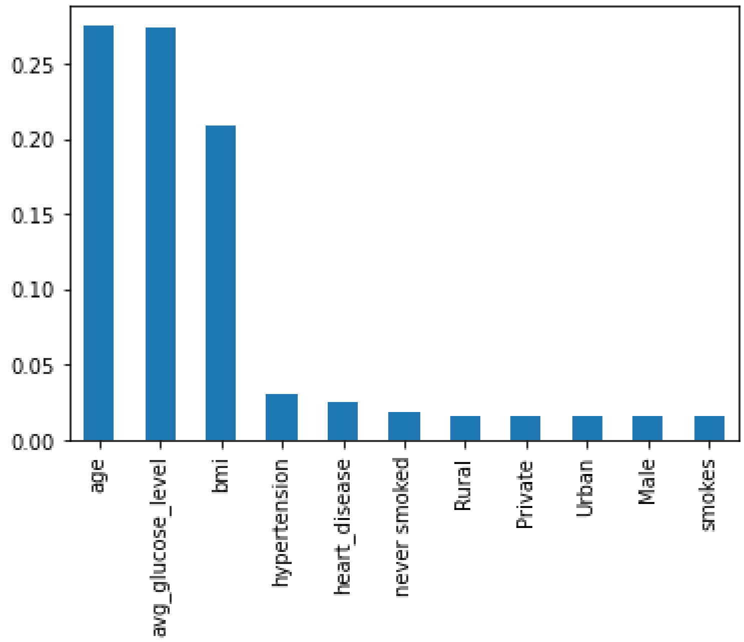
In [69]:
```
model.feature_importances_  # compute the scores
```

Out[69]:
```
array([1.50852334e-02, 1.57031462e-02, 3.16749387e-07, 2.75320681e-01,
       3.09127149e-02, 2.56070155e-02, 7.89691909e-03, 9.16796271e-03,
       1.23054746e-02, 1.85154504e-05, 1.60240539e-02, 1.40040020e-02,
       1.21828391e-03, 1.64421777e-02, 1.59429318e-02, 2.73874067e-01,
       2.09193574e-01, 1.28708345e-02, 1.46831578e-02, 1.81327448e-02,
       1.55961921e-02])
```

In [70]:
```
ranked_features = pd.Series(model.feature_importances_, index = X.columns)  # put
```

In [71]:
```
ranked_features.nlargest(11).plot(kind='bar')  # rank and plot the scores
```

Out[71]: <AxesSubplot:>



Mutual Information Gain

In [72]:
```
mu_ifo = mutual_info_classif(X,y)
```

In [73]:
```
mu_data = pd.Series(mu_ifo, index = X.columns)
mu_data.sort_values(ascending=False)
```

Out[73]:
```
age                  0.036125
Yes                  0.008051
avg_glucose_level    0.006257
heart_disease        0.006204
hypertension         0.005150
children             0.005073
bmi                  0.004936
No                   0.004766
Urban                0.004236
Other                0.001745
Govt_job             0.001648
Female               0.001321
Never_worked         0.000705
Private              0.000494
formerly smoked      0.000453
Rural                0.000000
Self-employed        0.000000
Male                 0.000000
Unknown              0.000000
never smoked         0.000000
smokes               0.000000
dtype: float64
```

In [74]:
```
x_train,x_test,y_train,y_test = train_test_split(X,y, test_size = 0.2, random_sta
```

In [75]:
```
def classify(model, x, y):
    x_train,x_test,y_train,y_test = train_test_split(X,y, test_size = 0.2, randon
    model.fit(x_train,y_train)
    print('Accuracy is: ', model.score(x_test,y_test)*100)
    score = cross_val_score(model,x,y,cv=5)                # we set the number
    print('Cross validation Accuaracy: ', np.mean(score)*100)
```

In [76]:
```
LG_model = LogisticRegression()    #making logistic regression model
classify(LG_model, X,y)
```

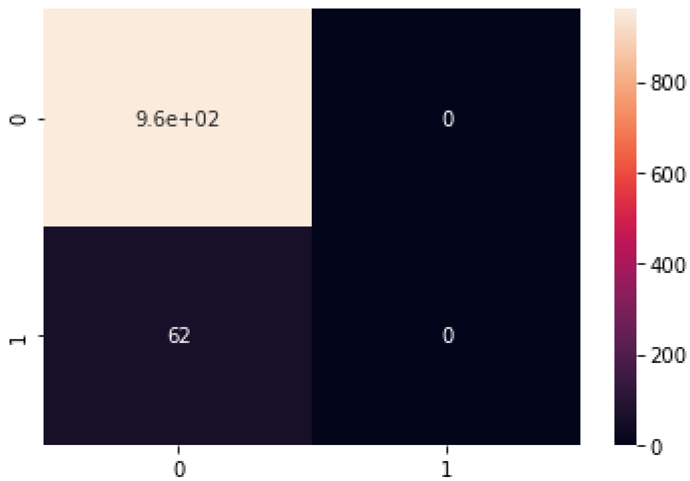
```
Accuracy is:  93.9334637964775
Cross validation Accuaracy:  95.12720156555773
```

In [77]:
```
y_pred = LG_model.predict(x_test)
```

In [78]:
```
cm = confusion_matrix(y_test,y_pred)
```

In [79]:
```
sns.heatmap(cm,annot=True)
```

Out[79]: <AxesSubplot:>



In [80]:
```
knn_model = KNeighborsClassifier(n_neighbors=5)
classify(knn_model,X,y)
```

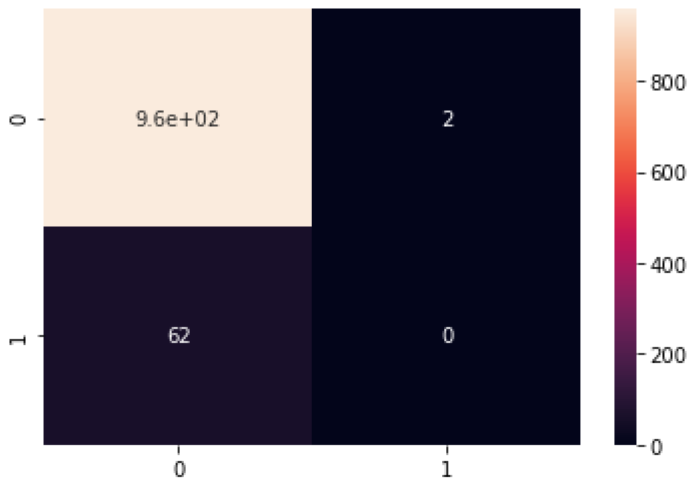
```
Accuracy is:  93.73776908023484
Cross validation Accuaracy:  94.28571428571428
```

In [81]:
```
y_pred = knn_model.predict(x_test)
```

In [82]:
```
cm = confusion_matrix(y_test,y_pred)
```

In [83]:
```
sns.heatmap(cm,annot=True)
```

Out[83]: <AxesSubplot:>



In [84]:
```
SVC_model = SVC(kernel='linear', C = 1)
classify(SVC_model, X,y)
```

```
Accuracy is:  93.9334637964775
Cross validation Accuaracy:  95.12720156555773
```

In [85]:
```
SVC_model = SVC(kernel='linear', C = 1)
```

In [86]:
```
SVC_model.fit(x_train,y_train)
```

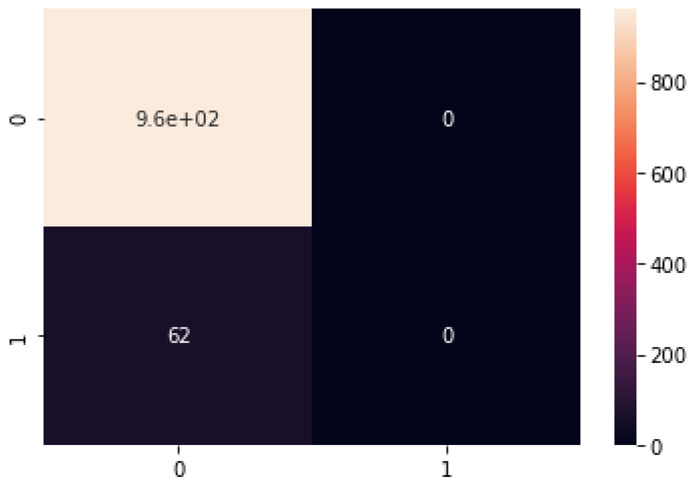
Out[86]: SVC(C=1, kernel='linear')

In [87]:
```
y_pred = SVC_model.predict(x_test) # save predictions in y_pred
```

In [88]:
```
cm = confusion_matrix(y_test,y_pred)
```

In [89]:
```
sns.heatmap(cm,annot=True) # plots the confusion matrix
```

Out[89]: <AxesSubplot:>



Trying the same process using Label Encoding

In [90]:
```
train_data
```

Out[90]:

	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
...	...	...	...	...	...	...	...	...
5105	18234	Female	80.0	1	0	Yes	Private	Urban
5106	44873	Female	81.0	0	0	Yes	Self-employed	Urban
5107	19723	Female	35.0	0	0	Yes	Self-employed	Rural
5108	37544	Male	51.0	0	0	Yes	Private	Rural
5109	44679	Female	44.0	0	0	Yes	Govt_job	Urban

5110 rows × 12 columns

In [91]:
```
cols = ['gender','ever_married', 'work_type','Residence_type','smoking_status']
le = LabelEncoder()                       # initialising the necessary function t
for col in cols:
    train_data[col] = le.fit_transform(train_data[col])
```

In [92]:
```
train_data
```

Out[92]:

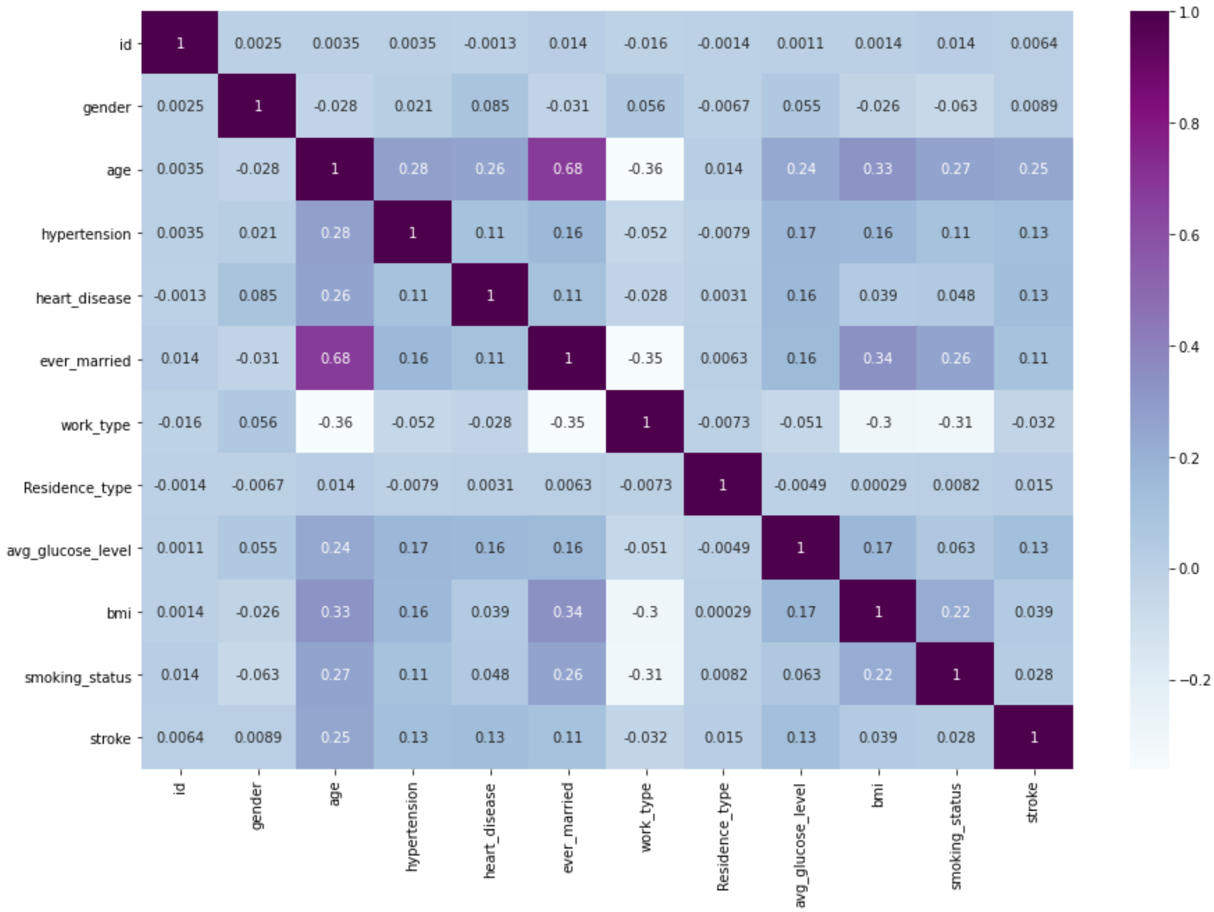
	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type
0	9046	1	67.0	0	1	1	2	1
1	51676	0	61.0	0	0	1	3	0
2	31112	1	80.0	0	1	1	2	0
3	60182	0	49.0	0	0	1	2	1
4	1665	0	79.0	1	0	1	3	0
...	...	...	...	...	...	...	...	...
5105	18234	0	80.0	1	0	1	2	1
5106	44873	0	81.0	0	0	1	3	1
5107	19723	0	35.0	0	0	1	3	0
5108	37544	1	51.0	0	0	1	2	0
5109	44679	0	44.0	0	0	1	0	1

5110 rows × 12 columns

In [93]:
```
corr=train_data.corr()
```

In [94]:
```
plt.figure(figsize=(15,10))
sns.heatmap(corr, annot = True, cmap="BuPu")
```

Out[94]: <AxesSubplot:>



In [95]:
```
A = train_data.drop(['stroke'],axis=1)
b = train_data['stroke']
```

In [96]:
```
kbest = SelectKBest(score_func = chi2, k = 'all') # target number of features is
ordered_features = kbest.fit(A,b)
```

In [97]:
```
df_scores = pd.DataFrame(ordered_features.scores_, columns=['Score'])
```

In [98]:
```
df_columns = pd.DataFrame(X.columns, columns = ['Feature_name'])
```

In [99]:
```
feature_rank = pd.concat([df_scores,df_columns],axis=1)
```

In [100]:
```
feature_rank.nlargest(12,'Score')
```

Out[100]:

	Score	Feature_name
2	3635.226911	Other
0	2556.735918	Female
8	1718.285446	Govt_job
4	87.987436	hypertension
3	75.449498	age
5	20.622787	heart_disease
9	15.879229	Never_worked
10	3.369423	Private
6	2.925901	No
7	0.600717	Yes
1	0.239001	Male

In [101]:
```
model = ExtraTreesClassifier()
model.fit(A,b)
```

Out[101]:
```
ExtraTreesClassifier()
```

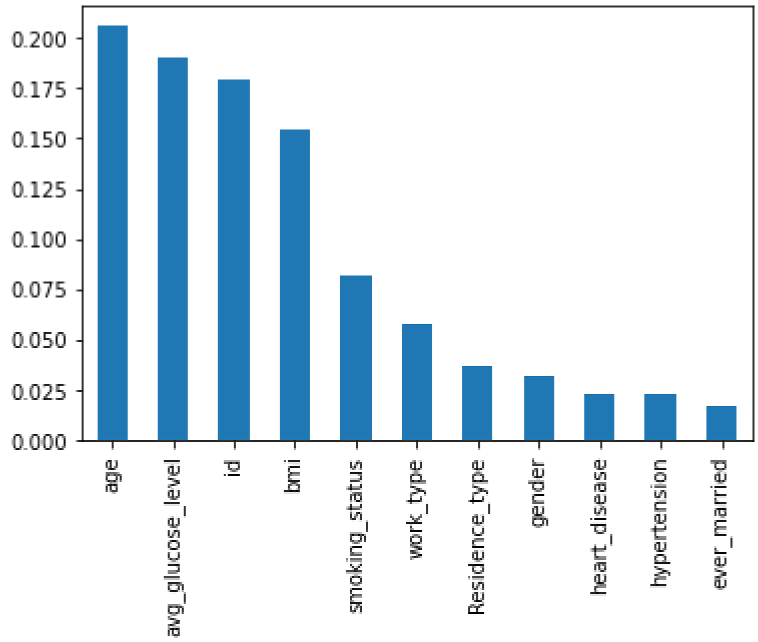
In [102]:
```
model.feature_importances_
```

Out[102]:
```
array([0.17932645, 0.03142367, 0.20624864, 0.02317516, 0.02318449,
       0.01660314, 0.05738771, 0.03673533, 0.19037076, 0.15401823,
       0.08152642])
```

In [103]:
```
ranked_features = pd.Series(model.feature_importances_, index = A.columns)
```

In [104]:
```
ranked_features.nlargest(12).plot(kind='bar')  # rank and plot the scores
```

Out[104]: <AxesSubplot:>



In [105]:
```
mu_ifo = mutual_info_classif(A,b)
mu_data = pd.Series(mu_ifo, index = A.columns)
mu_data.sort_values(ascending=False)
```

Out[105]:
```
age                  0.034894
work_type            0.011995
heart_disease        0.010218
bmi                  0.008821
smoking_status       0.007195
id                   0.005207
avg_glucose_level    0.005163
hypertension         0.004164
ever_married         0.001049
Residence_type       0.001045
gender               0.000000
dtype: float64
```

In [106]:
```
a_train,a_test,b_train,b_test = train_test_split(A,b, test_size = 0.2, random_sta
```

In [107]:
```
def classify(model, a, b):
    a_train,x_test,b_train,b_test = train_test_split(A,b, test_size = 0.2, randon
    model.fit(a_train,b_train)
    print('Accuracy is: ', model.score(a_test,b_test)*100)
    score = cross_val_score(model,a,b,cv=5)                    # we set the number
    print('Cross validation Accuaracy: ', np.mean(score)*100)
```

In [108]:
```

LG_model = LogisticRegression()
classify(LG_model, A,b)
```

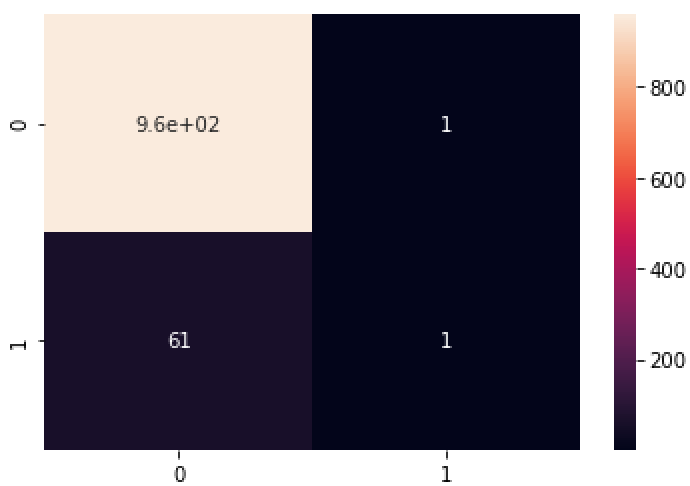
```
Accuracy is:  93.9334637964775
Cross validation Accuaracy:  95.06849315068493
```

In [109]:
```
b_pred = LG_model.predict(a_test)
```

In [110]:
```
com = confusion_matrix(b_test,b_pred)
```

In [111]:
```
sns.heatmap(com,annot=True) # plots the confusion matrix
```

Out[111]: <AxesSubplot:>



In [112]:
```

knn_model = KNeighborsClassifier(n_neighbors=5)
classify(knn_model,A,b)
```

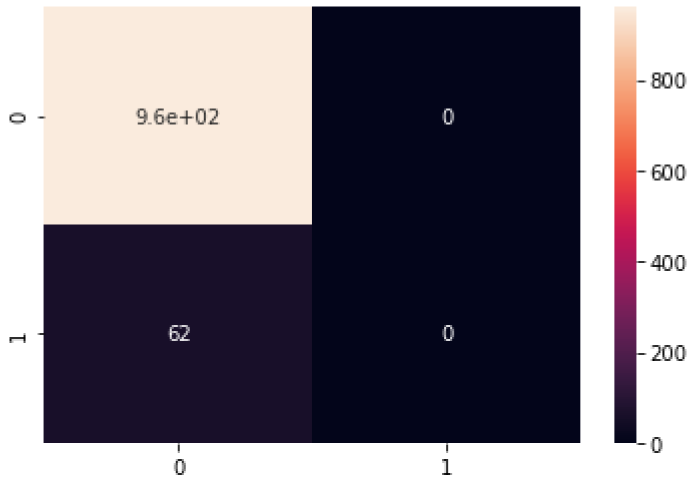
```
Accuracy is:  93.9334637964775
Cross validation Accuaracy:  95.12720156555773
```

In [113]:
```
b_pred = knn_model.predict(a_test)
```

In [114]:
```
com = confusion_matrix(b_test,b_pred)
```

In [115]:
```
sns.heatmap(com,annot=True) # plots the confusion matrix
```

Out[115]: <AxesSubplot:>



In [116]:
```
SVC_model = SVC(kernel='linear', C = 1)
classify(SVC_model, A,b)
```

```
Accuracy is:  93.34637964774952
Cross validation Accuaracy:  94.28571428571428
```

In [117]:
```
SVC_model = SVC(kernel='linear', C = 1)
```

In [118]:
```
SVC_model.fit(a_train,b_train)
```

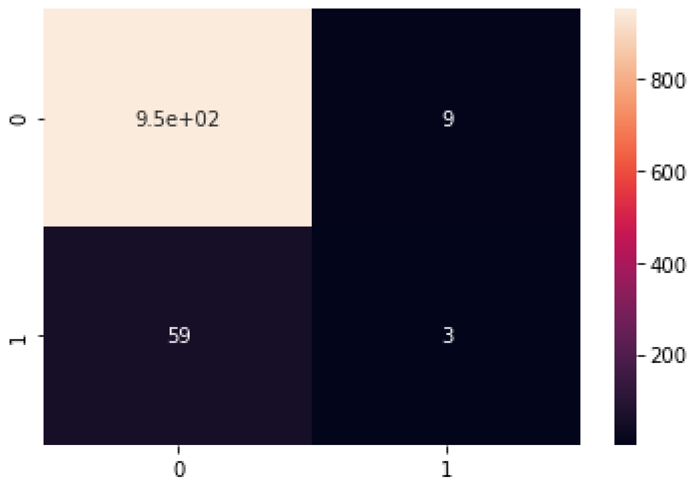
Out[118]: SVC(C=1, kernel='linear')

In [119]:
```
b_pred = SVC_model.predict(a_test) # save predictions in y_pred
```

In [120]:
```
com = confusion_matrix(b_test,b_pred)
```

In [121]:
```
sns.heatmap(com,annot=True) # plots the confusion matrix
```

Out[121]: <AxesSubplot:>



THANK YOU

In [ ]: