Problem Statement: This dataset is used to predict whether a person can suffer from a stroke based on the input parameters like gender, age, maritial status,work type,residence type , different health Issues, and smoking status.

In [158]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from sklearn.datasets import load_digits
from sklearn.linear_model import Perceptron
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_curve, auc
from sklearn import preprocessing
import warnings
warnings.filterwarnings("ignore")
```

In [186]:

```
df=pd.read_csv('Stroke.csv')
df.head()
```

Out[186]:

	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 [187]:

```
df.info()
```

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

Preprocessing

In [188]:

```
df.drop(columns=['id'], inplace=True)
```

In [189]:

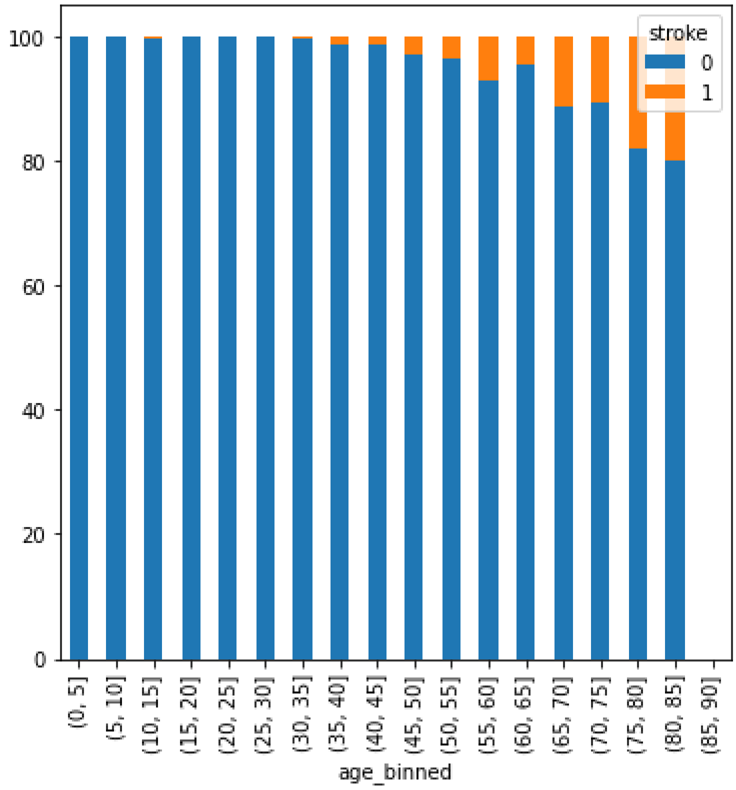
```
df = df[df['bmi'].notna()]
```

In [190]:

```
df['age_binned'] = pd.cut(df['age'], np.arange(0, 91, 5)).cat.codes
df['bmi_binned'] = pd.cut(df['bmi'], np.arange(0, 101, 5)).cat.codes
```

In [191]:

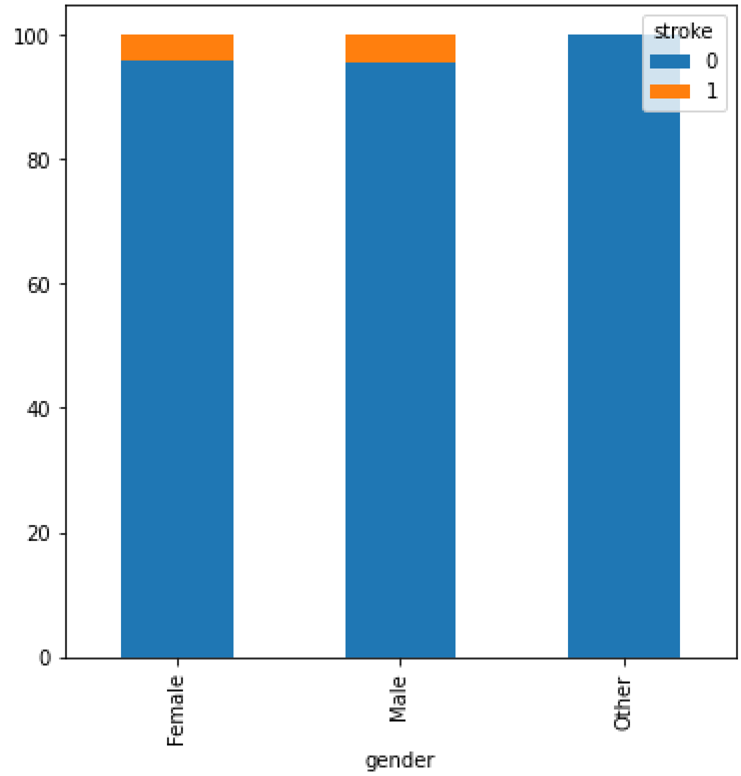
```
# Get the count of records by age_binned and stroke
df_breakdown = df.groupby(['age_binned', 'stroke'])['age'].count()
# Get the count of records by age_binned
df_total = df.groupby(['age_binned'])['age'].count()
# Get the percentage for 100% stacked bar chart
df_pct = df_breakdown / df_total * 100
# Create proper DataFrame's format
df_pct = df_pct.unstack()
df_pct.plot.bar(stacked=True, figsize=(6,6));
```



Observation: Old people are more likely to suffer from a stroke compared to young people patient.

In [192]:

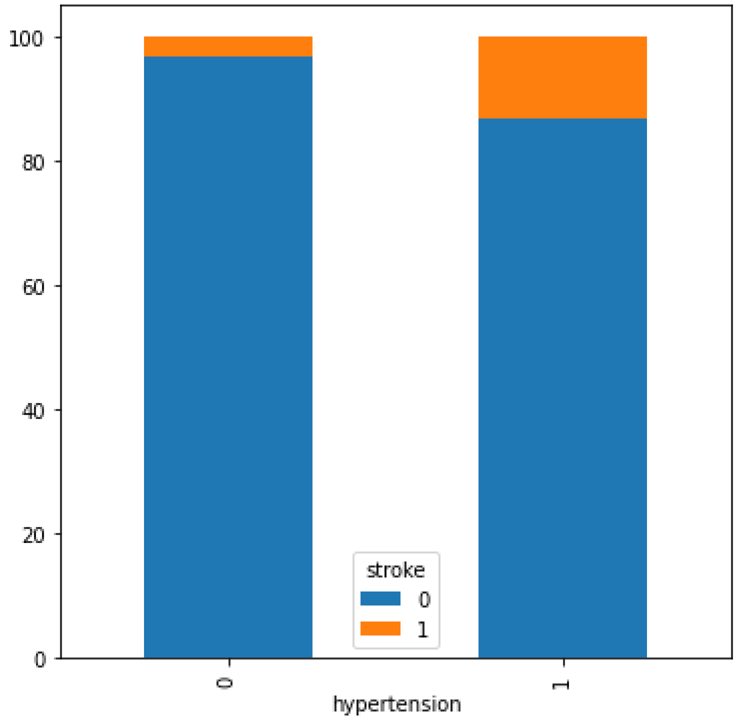
```
 # Get the count of records by gender and stroke
df_breakdown = df.groupby(['gender', 'stroke'])['age'].count()
# Get the count of records by gender
df_total = df.groupby(['gender'])['age'].count()
# Get the percentage for 100% stacked bar chart
df_pct = df_breakdown / df_total * 100
# Create proper DataFrame's format
df_pct = df_pct.unstack()
df_pct.plot.bar(stacked=True, figsize=(6,6));
```



Observation: Gender Does not show much variation, Both Male and Female have equal chances of having stroke.

In [193]:

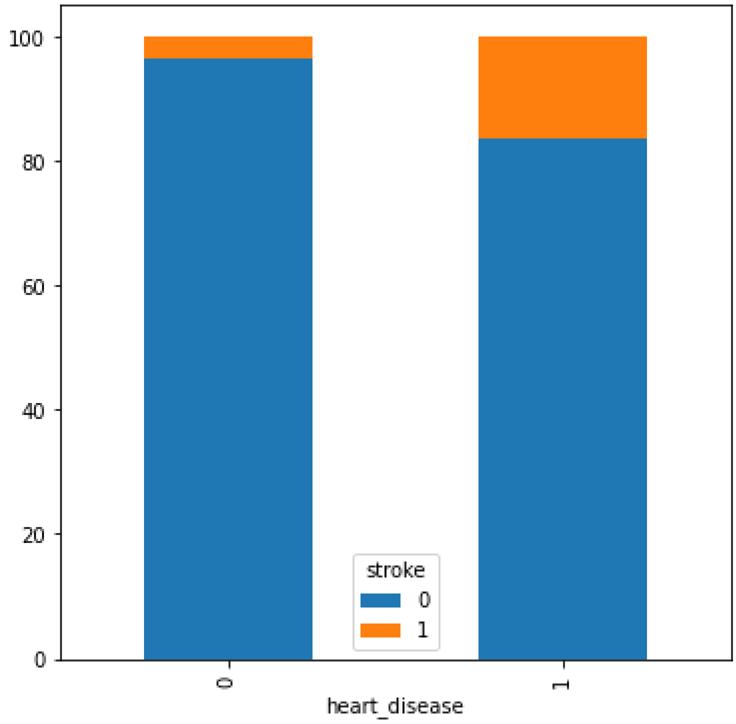
```
# Get the count of records by hypertension and stroke
df_breakdown = df.groupby(['hypertension', 'stroke'])['age'].count()
# Get the count of records by hypertension
df_total = df.groupby(['hypertension'])['age'].count()
# Get the percentage for 100% stacked bar chart
df_pct = df_breakdown / df_total * 100
# Create proper DataFrame's format
df_pct = df_pct.unstack()
df_pct.plot.bar(stacked=True, figsize=(6,6));
```



Observation: People with HyperTension has higher chances of stroke

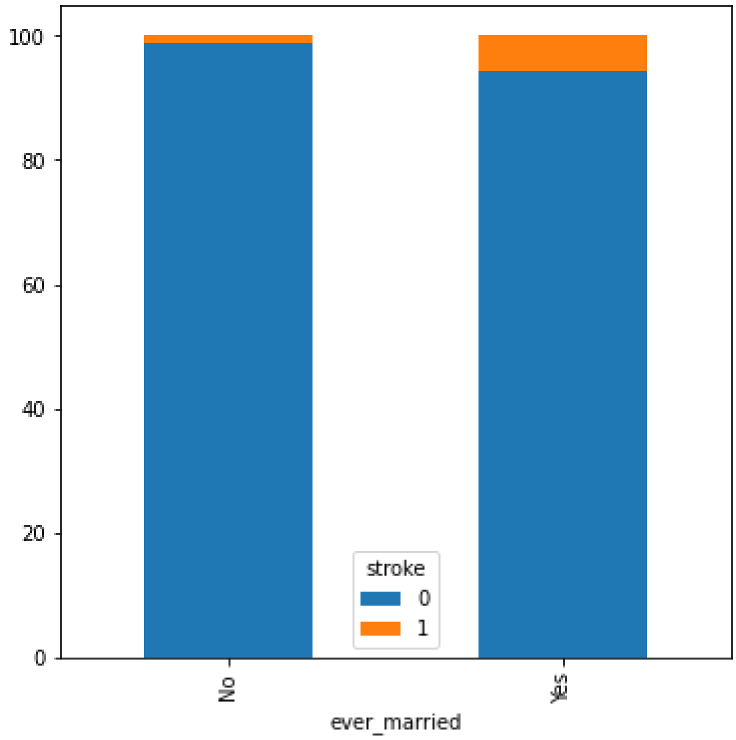
In [194]:

```
# Get the count of records by heart_disease and stroke
df_breakdown = df.groupby(['heart_disease', 'stroke'])['age'].count()
# Get the count of records by heart_disease
df_total = df.groupby(['heart_disease'])['age'].count()
# Get the percentage for 100% stacked bar chart
df_pct = df_breakdown / df_total * 100
# Create proper DataFrame's format
df_pct = df_pct.unstack()
df_pct.plot.bar(stacked=True, figsize=(6,6));
```



In [195]:

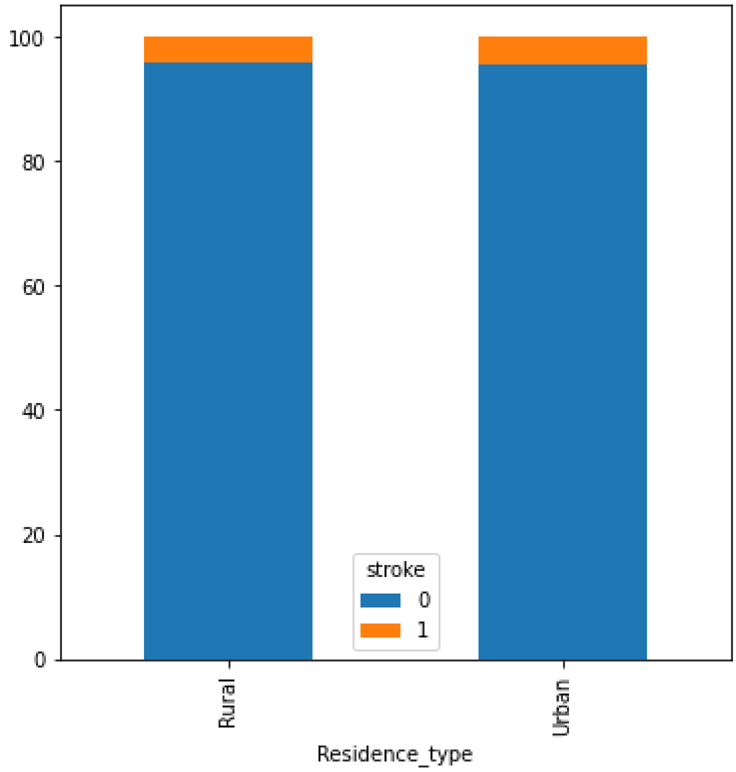
```
# Get the count of records by ever_married and stroke
df_breakdown = df.groupby(['ever_married', 'stroke'])['age'].count()
# Get the count of records by ever_married
df_total = df.groupby(['ever_married'])['age'].count()
# Get the percentage for 100% stacked bar chart
df_pct = df_breakdown / df_total * 100
# Create proper DataFrame's format
df_pct = df_pct.unstack()
df_pct.plot.bar(stacked=True, figsize=(6,6));
```



Observation: From the analysis it can be said married people suffer from stroke more, but again that is a fact that married people are older in age compared to unmarried so we cannot infer anything from it.

In [196]:

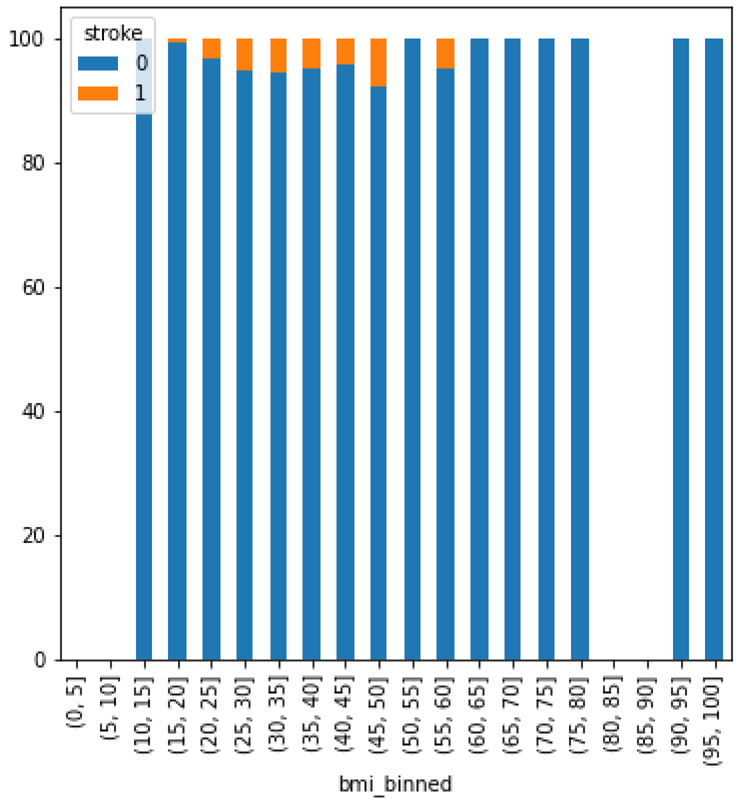
```
# Get the count of records by Residence_type and stroke
df_breakdown = df.groupby(['Residence_type', 'stroke'])['age'].count()
# Get the count of records by Residence_type
df_total = df.groupby(['Residence_type'])['age'].count()
# Get the percentage for 100% stacked bar chart
df_pct = df_breakdown / df_total * 100
# Create proper DataFrame's format
df_pct = df_pct.unstack()
df_pct.plot.bar(stacked=True, figsize=(6,6));
```



Observation: People from Rural areas as well as urban areas both suffer from strokes equally

In [197]:

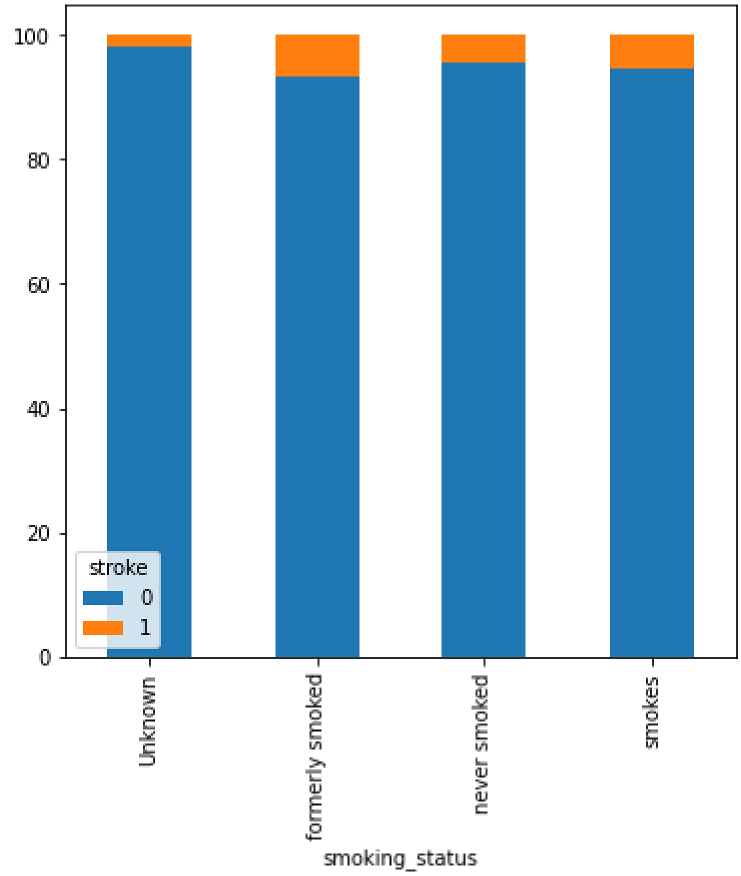
```
# Get the count of records by bmi_binned and stroke
df_breakdown = df.groupby(['bmi_binned', 'stroke'])['age'].count()
# Get the count of records by bmi_binned
df_total = df.groupby(['bmi_binned'])['age'].count()
# Get the percentage for 100% stacked bar chart
df_pct = df_breakdown / df_total * 100
# Create proper DataFrame's format
df_pct = df_pct.unstack()
df_pct.plot.bar(stacked=True, figsize=(6,6));
```



Observation: People with BMI 45-50 suffer more from stroke

In [198]:

```
# Get the count of records by smoking_status and stroke
df_breakdown = df.groupby(['smoking_status', 'stroke'])['age'].count()
# Get the count of records by smoking_status
df_total = df.groupby(['smoking_status'])['age'].count()
# Get the percentage for 100% stacked bar chart
df_pct = df_breakdown / df_total * 100
# Create proper DataFrame's format
df_pct = df_pct.unstack()
df_pct.plot.bar(stacked=True, figsize=(6,6));
```



Observation: Even the Non Smokers can get a stroke so Smoking does not make any difference in chances of getting a stroke.

For Better Prediction we will convert the categorial data into numbers

In [172]:

```
df[['gender']] = df[['gender']].apply(lambda col:pd.Categorical(col).codes)
df[['ever_married']] = df[['ever_married']].apply(lambda col:pd.Categorical(col).codes)
df[['work_type']] = df[['work_type']].apply(lambda col:pd.Categorical(col).codes)
df[['Residence_type']] = df[['Residence_type']].apply(lambda col:pd.Categorical(col).codes)
df[['smoking_status']] = df[['smoking_status']].apply(lambda col:pd.Categorical(col).codes)
```

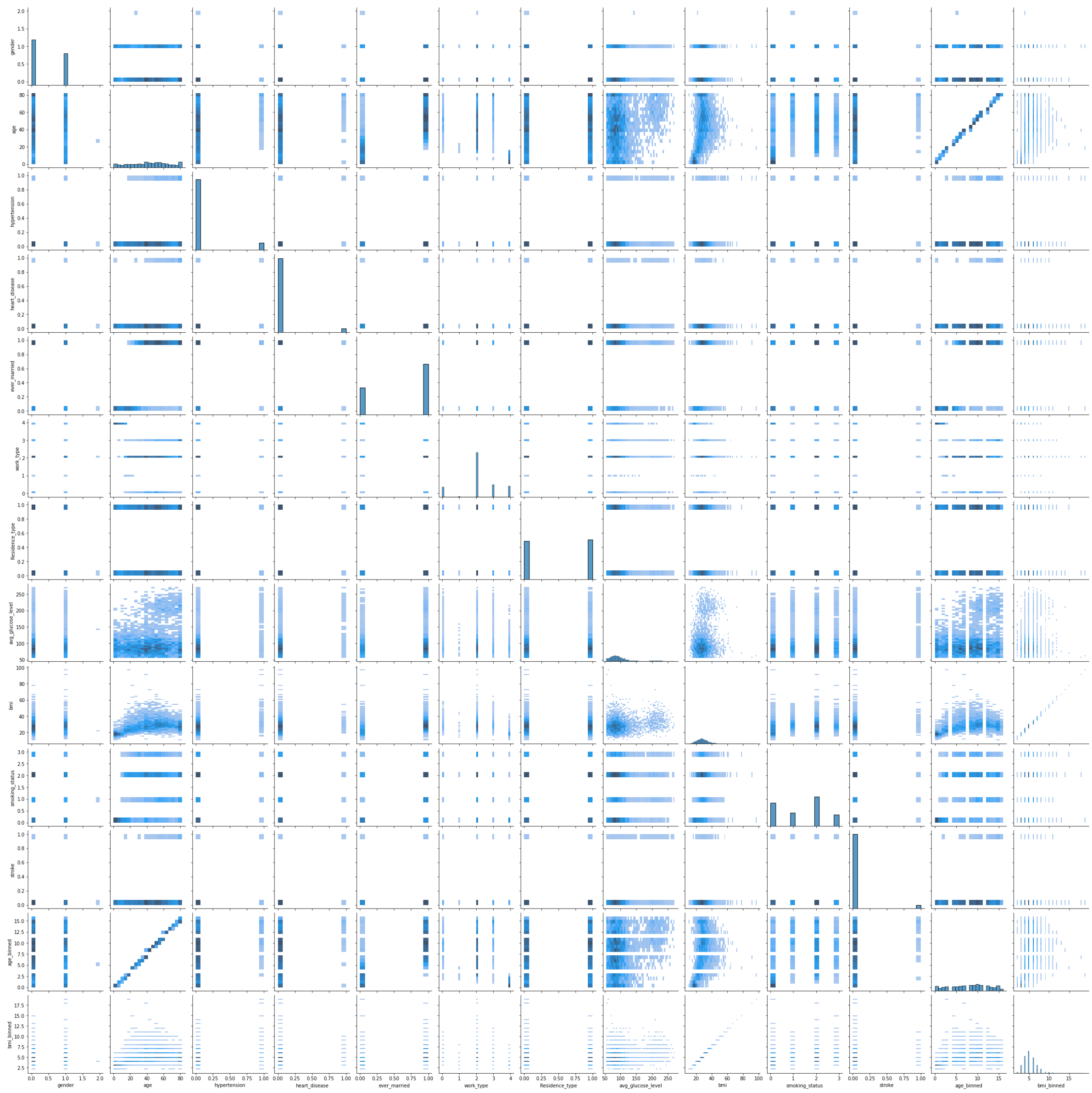
bivariate analysis

In [173]:

```
sns.pairplot(df, kind="hist")
```

Out[173]:

```
<seaborn.axisgrid.PairGrid at 0x1e3f063fbb0>
```



As the data set contains mainly binary values and the strength is also week as we can see so it is hard to find corelation using the pairplot

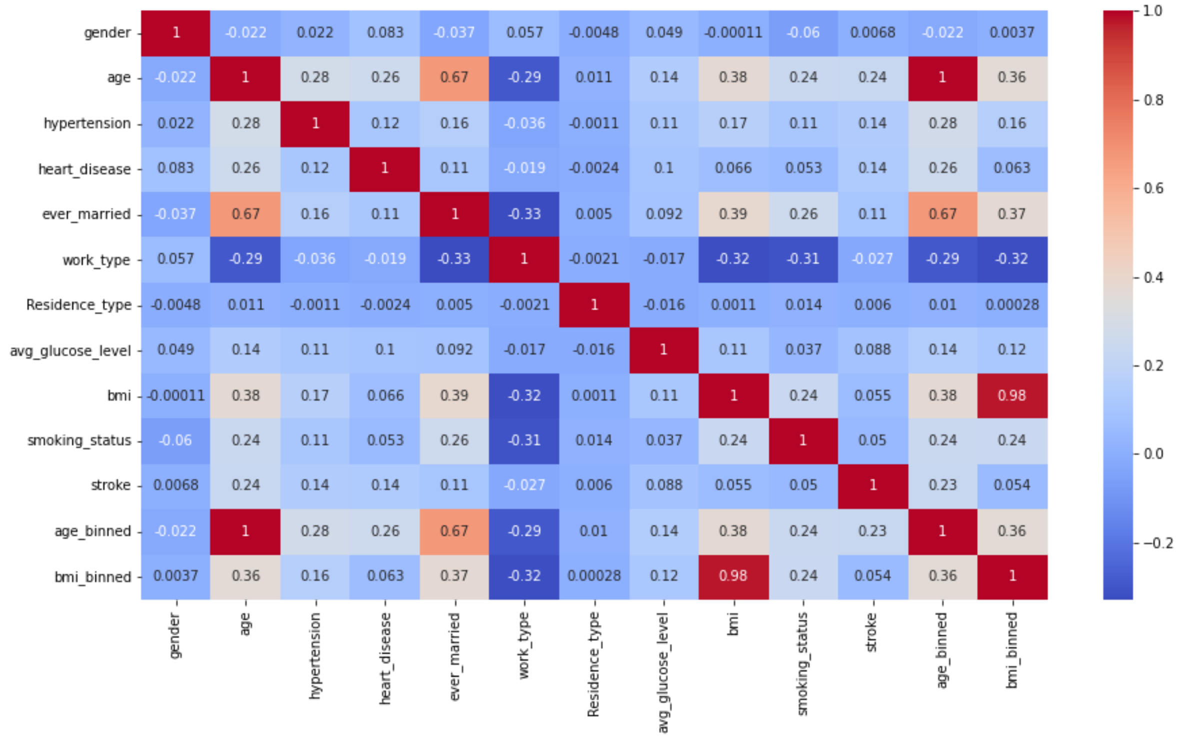
In the dataset Variable are ordinal; numeric,and categorical. . Variables are related nonlinearly . Data is non-normally distributed so best option to find co relation is Spearman's Rank Correlation.

In [174]:

```
plt.figure(figsize = (15,8))
sns.heatmap(df.corr(method='spearman'),cmap='coolwarm',annot=True)
```

Out[174]:

```
<AxesSubplot:>
```



As we can see in the generated heatMap there is not much co relation seen in the data set except between ever_married and age.

In [175]:

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

In [176]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=6)
print(X_train.shape,X_test.shape,X.shape)
```

```
(3927, 12) (982, 12) (4909, 12)
```

In [177]:

```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline
from sklearn.linear_model import LinearRegression
from sklearn import metrics
```

In [178]:

```
poly_model = make_pipeline(PolynomialFeatures(degree=1,include_bias=True),
                           LinearRegression())
X_train = np.asarray(X_train)
y_train = np.asarray(y_train)

X_test = np.asarray(X_test)
y_test = np.asarray(y_test)

poly_model.fit(X_train, y_train)
```

Out[178]:

```
Pipeline(steps=[('polynomialfeatures', PolynomialFeatures(degree=1)),
                ('linearregression', LinearRegression())])
```

In this data set we are most values are binary so Classification model is the best one to be used as Classification algorithms are used to predict/Classify the discrete values and When there are only two classes it is best to use Logistic regression Classification

In [179]:

```
clf2 = LogisticRegression(random_state=0).fit(X_train, y_train)
```

In [180]:

```
clf2.predict(X_test)
clf2.predict_proba(X_test)
y_pred2 = clf2.predict(X_test)

score=clf2.score(X_test, y_test)
print(score)
```

```
0.955193482688391
```

In [181]:

```
print('MAE:', metrics.mean_absolute_error(y_test, y_pred2))
print('MSE:', metrics.mean_squared_error(y_test, y_pred2))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, y_pred2)))
```

```
MAE: 0.04480651731160896
MSE: 0.04480651731160896
RMSE: 0.21167550002683105
```

In [182]:

```
confusion_mat = confusion_matrix(y_test, y_pred2)
print(confusion_mat)
```

```
[[938   0]
 [ 44   0]]
```

In [183]:

```
print(classification_report(y_test, y_pred2))
```

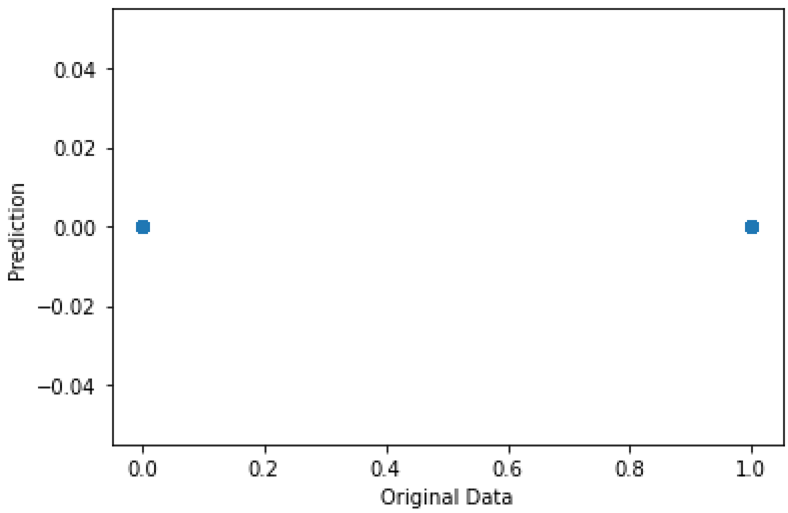
```
              precision    recall  f1-score   support

           0       0.96      1.00      0.98       938
           1       0.00      0.00      0.00        44

    accuracy                           0.96       982
   macro avg       0.48      0.50      0.49       982
weighted avg       0.91      0.96      0.93       982
```

In [184]:

```
plt.scatter(y_test, y_pred2)
plt.xlabel("Original Data")
plt.ylabel("Prediction")
```

Out[184]:

```
Text(0, 0.5, 'Prediction')
```



HeatMap of Confussion Matrix

In [185]:

```
plt.figure(figsize = (15,8))
group_names = ['True Neg','False Pos','False Neg','True Pos']
group_counts = ["{0:0.0f}".format(value) for value in
                confusion_mat.flatten()]
group_percentages = ["{0:.2%}".format(value) for value in
                     confusion_mat.flatten()/np.sum(confusion_mat)]
labels = [f"{v1}\n{v2}\n{v3}" for v1, v2, v3 in
          zip(group_names,group_counts,group_percentages)]
labels = np.asarray(labels).reshape(2,2)
sns.heatmap(confusion_mat, annot=labels, fmt='', cmap='Blues')
```

Out[185]:

```
<AxesSubplot:>
```