In [34]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
```

In [35]:

```
df=pd.read_csv("C:\\Users\\swast\\Desktop\\verzeo internship\\outstanding projects\healthcare-dataset-stroke-data.csv")
```

In [36]:

```
df.head(50)
```

Out[36]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smo
0	9046	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	NaN	ne
2	31112	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	ne
3	60182	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	ne
5	56669	Male	81.0	0	0	Yes	Private	Urban	186.21	29.0	
6	53882	Male	74.0	1	1	Yes	Private	Rural	70.09	27.4	ne
7	10434	Female	69.0	0	0	No	Private	Urban	94.39	22.8	ne
8	27419	Female	59.0	0	0	Yes	Private	Rural	76.15	NaN	
9	60491	Female	78.0	0	0	Yes	Private	Urban	58.57	24.2	
10	12109	Female	81.0	1	0	Yes	Private	Rural	80.43	29.7	ne
11	12095	Female	61.0	0	1	Yes	Govt_job	Rural	120.46	36.8	
12	12175	Female	54.0	0	0	Yes	Private	Urban	104.51	27.3	
13	8213	Male	78.0	0	1	Yes	Private	Urban	219.84	NaN	
14	5317	Female	79.0	0	1	Yes	Private	Urban	214.09	28.2	ne
15	58202	Female	50.0	1	0	Yes	Self-employed	Rural	167.41	30.9	ne
16	56112	Male	64.0	0	1	Yes	Private	Urban	191.61	37.5	
17	34120	Male	75.0	1	0	Yes	Private	Urban	221.29	25.8	
18	27458	Female	60.0	0	0	No	Private	Urban	89.22	37.8	ne
19	25226	Male	57.0	0	1	No	Govt_job	Urban	217.08	NaN	
20	70630	Female	71.0	0	0	Yes	Govt_job	Rural	193.94	22.4	
21	13861	Female	52.0	1	0	Yes	Self-employed	Urban	233.29	48.9	ne
22	68794	Female	79.0	0	0	Yes	Self-employed	Urban	228.70	26.6	ne

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smo
23	64778	Male	82.0	0	1	Yes	Private	Rural	208.30	32.5	
24	4219	Male	71.0	0	0	Yes	Private	Urban	102.87	27.2	
25	70822	Male	80.0	0	0	Yes	Self-employed	Rural	104.12	23.5	ne
26	38047	Female	65.0	0	0	Yes	Private	Rural	100.98	28.2	
27	61843	Male	58.0	0	0	Yes	Private	Rural	189.84	NaN	
28	54827	Male	69.0	0	1	Yes	Self-employed	Urban	195.23	28.3	
29	69160	Male	59.0	0	0	Yes	Private	Rural	211.78	NaN	
30	43717	Male	57.0	1	0	Yes	Private	Urban	212.08	44.2	
31	33879	Male	42.0	0	0	Yes	Private	Rural	83.41	25.4	
32	39373	Female	82.0	1	0	Yes	Self-employed	Urban	196.92	22.2	ne
33	54401	Male	80.0	0	1	Yes	Self-employed	Urban	252.72	30.5	
34	14248	Male	48.0	0	0	No	Govt_job	Urban	84.20	29.7	ne
35	712	Female	82.0	1	1	No	Private	Rural	84.03	26.5	
36	47269	Male	74.0	0	0	Yes	Private	Rural	219.72	33.7	
37	24977	Female	72.0	1	0	Yes	Private	Rural	74.63	23.1	
38	47306	Male	58.0	0	0	No	Private	Rural	92.62	32.0	
39	62602	Female	49.0	0	0	Yes	Private	Urban	60.91	29.9	ne
40	4651	Male	78.0	0	0	Yes	Private	Rural	78.03	23.9	
41	1261	Male	54.0	0	0	Yes	Private	Urban	71.22	28.5	ne
42	61960	Male	82.0	0	1	Yes	Private	Urban	144.90	26.4	
43	1845	Female	63.0	0	0	Yes	Private	Urban	90.90	NaN	
44	7937	Male	60.0	1	0	Yes	Govt_job	Urban	213.03	20.2	
45	19824	Male	76.0	1	0	Yes	Private	Rural	243.58	33.6	ne
46	37937	Female	75.0	0	1	No	Self-employed	Urban	109.78	NaN	
47	47472	Female	58.0	0	0	Yes	Private	Urban	107.26	38.6	
48	35626	Male	81.0	0	0	Yes	Self-employed	Urban	99.33	33.7	ne
49	36338	Female	39.0	1	0	Yes	Private	Rural	58.09	39.2	

In [37]:

```
df.info()
df.columns
```

```
<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
```

Out[37]:

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

In [38]:

```
df.describe()
```

Out[38]:

	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

In [39]:

```
df.isna().sum()
```

Out[39]:

```
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 [40]:

```
df=df.dropna()
df.pop('id')
```

Out[40]:

```
0        9046
2       31112
3       60182
4        1665
5       56669
        ...
```

```
5104    14180
5106    44873
5107    19723
5108    37544
5109    44679
Name: id, Length: 4909, dtype: int64
```

In [41]:

```
df
```

Out[41]:

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_s
0	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	for sn
2	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never sn
3	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	sn
4	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never sn
5	Male	81.0	0	0	Yes	Private	Urban	186.21	29.0	for sn
...	...	...	...	...	...	...	...	...	...	
5104	Female	13.0	0	0	No	children	Rural	103.08	18.6	Unk
5106	Female	81.0	0	0	Yes	Self-employed	Urban	125.20	40.0	never sn
5107	Female	35.0	0	0	Yes	Self-employed	Rural	82.99	30.6	never sn
5108	Male	51.0	0	0	Yes	Private	Rural	166.29	25.6	for sn
5109	Female	44.0	0	0	Yes	Govt_job	Urban	85.28	26.2	Unk

4909 rows × 11 columns

In [42]:

```
df=df.dropna()
```

In [43]:

```
df2=pd.get_dummies(df, drop_first=True)
print(df2.head(20))
df2.columns
```

```
     age  hypertension  heart_disease  avg_glucose_level   bmi  stroke  \
0   67.0             0              1             228.69  36.6       1
2   80.0             0              1             105.92  32.5       1
3   49.0             0              0             171.23  34.4       1
4   79.0             1              0             174.12  24.0       1
5   81.0             0              0             186.21  29.0       1
6   74.0             1              1              70.09  27.4       1
7   69.0             0              0              94.39  22.8       1
9   78.0             0              0              58.57  24.2       1
10  81.0             1              0              80.43  29.7       1
11  61.0             0              1             120.46  36.8       1
12  54.0             0              0             104.51  27.3       1
14  79.0             0              1             214.09  28.2       1
15  50.0             1              0             167.41  30.9       1
16  64.0             0              1             191.61  37.5       1
17  75.0             1              0             221.29  25.8       1
18  60.0             0              0              89.22  37.8       1
20  71.0             0              0             193.94  22.4       1
21  52.0             1              0             233.29  48.9       1
22  79.0             0              0             228.70  26.6       1
```

22	79.0	0	0	228.70	26.6	1
23	82.0	0	1	208.30	32.5	1

	gender_Male	gender_Other	ever_married_Yes	work_type_Never_worked	\
0	1	0	1	0	
2	1	0	1	0	
3	0	0	1	0	
4	0	0	1	0	
5	1	0	1	0	
6	1	0	1	0	
7	0	0	0	0	
9	0	0	1	0	
10	0	0	1	0	
11	0	0	1	0	
12	0	0	1	0	
14	0	0	1	0	
15	0	0	1	0	
16	1	0	1	0	
17	1	0	1	0	
18	0	0	0	0	
20	0	0	1	0	
21	0	0	1	0	
22	0	0	1	0	
23	1	0	1	0	

	work_type_Private	work_type_Self-employed	work_type_children	\
0	1	0	0	
2	1	0	0	
3	1	0	0	
4	0	1	0	
5	1	0	0	
6	1	0	0	
7	1	0	0	
9	1	0	0	
10	1	0	0	
11	0	0	0	
12	1	0	0	
14	1	0	0	
15	0	1	0	
16	1	0	0	
17	1	0	0	
18	1	0	0	
20	0	0	0	
21	0	1	0	
22	0	1	0	
23	1	0	0	

	Residence_type_Urban	smoking_status_formerly smoked	\
0	1	1	
2	0	0	
3	1	0	
4	0	0	
5	1	1	
6	0	0	
7	1	0	
9	1	0	
10	0	0	
11	0	0	
12	1	0	
14	1	0	
15	0	0	
16	1	0	
17	1	0	
18	1	0	
20	0	0	
21	1	0	
22	1	0	
23	0	0	

	smoking_status_never smoked	smoking_status_smokes
0	0	0
2	1	0
3	0	1

```
4                                  1                                  0
5                                  0                                  0
6                                  1                                  0
7                                  1                                  0
9                                  0                                  0
10                                 1                                  0
11                                 0                                  1
12                                 0                                  1
14                                 1                                  0
15                                 1                                  0
16                                 0                                  1
17                                 0                                  1
18                                 1                                  0
20                                 0                                  1
21                                 1                                  0
22                                 1                                  0
23                                 0                                  0
```

Out[43]:

```
Index(['age', 'hypertension', 'heart_disease', 'avg_glucose_level', 'bmi',
       'stroke', 'gender_Male', 'gender_Other', 'ever_married_Yes',
       'work_type_Never_worked', 'work_type_Private',
       'work_type_Self-employed', 'work_type_children', 'Residence_type_Urban',
       'smoking_status_formerly smoked', 'smoking_status_never smoked',
       'smoking_status_smokes'],
      dtype='object')
```

In [44]:

```
df.groupby(['stroke'],as_index=False).mean()
```

Out[44]:

	stroke	age	hypertension	heart_disease	avg_glucose_level	bmi
0	**0**	**41.760451**	**0.083191**	**0.043191**	**104.003736**	**28.823064**
1	**1**	**67.712919**	**0.287081**	**0.191388**	**134.571388**	**30.471292**

this gives us a basic idea that usually one suffering from a heart attack is older, and are more likely to have had hyper tension , heart disease and a glucose level and BMI higher than people who havent had a stroke

In [45]:

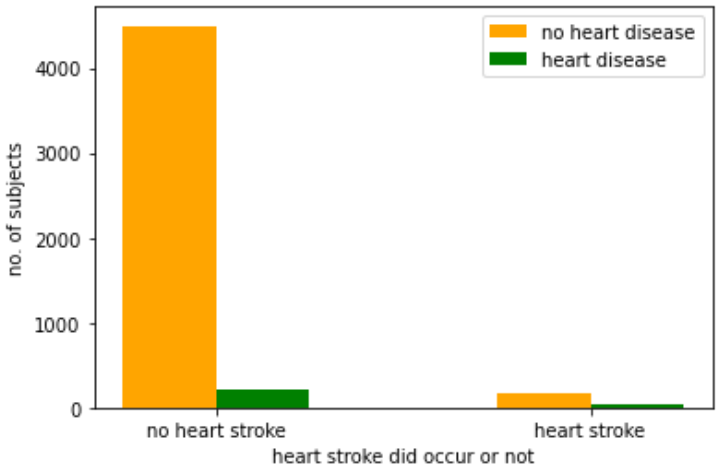
```
df1=(df.groupby(['stroke']).gender.value_counts().unstack())
df_hd=(df.groupby(['heart_disease']).stroke.value_counts().unstack())
df_wtP=(df2.groupby(['work_type_Private']).stroke.value_counts().unstack())
df_ssfs=(df2.groupby(['smoking_status_formerly smoked']).stroke.value_counts().unstack()
)
df_sss=(df2.groupby(['smoking_status_smokes']).stroke.value_counts().unstack())
df_ht=(df2.groupby(['hypertension']).stroke.value_counts().unstack())
```

In [46]:

```
print(df_hd)
plt.bar(('no heart stroke','heart stroke'),list(df_hd.iloc[0,:].values),-0.25,color='oran
ge',align='edge',label='no heart disease')
plt.bar(('no heart stroke','heart stroke'),list(df_hd.iloc[1,:].values),0.25,color='green
',align='edge',label='heart disease')
plt.xlabel('heart stroke did occur or not')
plt.ylabel('no. of subjects')
plt.legend()
percent=(169/(169+4497))*100
percent1=(40/243)*100
print('no heart disease subject having stroke has a chance of ',percent , '%\n heart dis
ease subject having stroke has a chance of ',percent1,'%')
```

```
stroke            0    1
heart_disease
0              4497  169
```

```
1                203   40
no heart disease subject having stroke has a chance of  3.621945992284612 %
 heart disease subject having stroke has a chance of  16.46090534979424 %
```



here we are observing an expected trend where normally a person having a heart disease has about 16% chance to be struck by a heart stroke which is about 13% higher than a normal person.

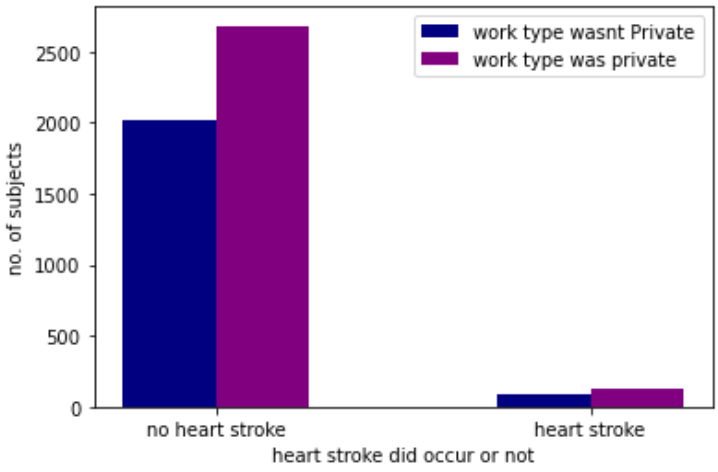
In [47]:

```
print(df_wtP)
plt.bar(('no heart stroke','heart stroke'),list(df_wtP.iloc[0,:].values),-0.25,color='navy',align='edge',label='work type wasnt Private')
plt.bar(('no heart stroke','heart stroke'),list(df_wtP.iloc[1,:].values),0.25,color='purple',align='edge',label='work type was private')
plt.xlabel('heart stroke did occur or not')
plt.ylabel('no. of subjects')
plt.legend()
```

```
stroke                0     1
work_type_Private
0                  2016    82
1                  2684   127
```

Out[47]:

```
<matplotlib.legend.Legend at 0x1cdf47807c0>
```



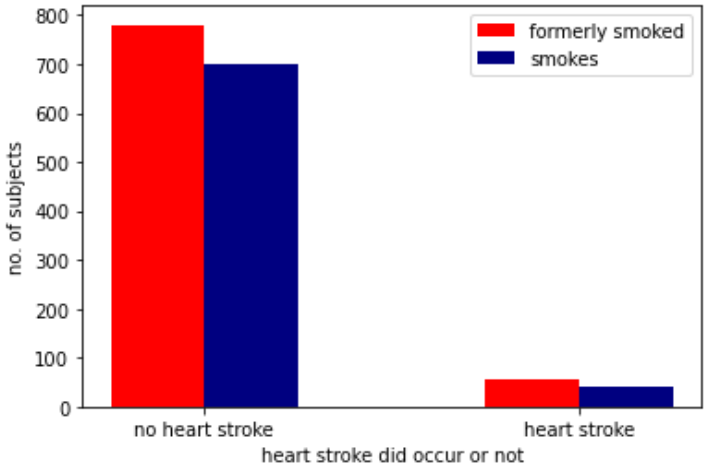
In [48]:

```
print(df_ssfs)
print(df_sss)
plt.bar(('no heart stroke','heart stroke'),list(df_ssfs.iloc[1,:].values),-0.25,color='red',align='edge',label='formerly smoked')
plt.bar(('no heart stroke','heart stroke'),list(df_sss.iloc[1,:].values),0.25,color='navy',align='edge',label='smokes')
plt.xlabel('heart stroke did occur or not')
plt.ylabel('no. of subjects')
plt.legend()
```

```
stroke                                0    1
smoking_status_formerly smoked
0                                  3920  152
1                                   780   57
stroke                        0    1
smoking_status_smokes
0                          4002  170
1                           698   39
```

Out[48]:

```
<matplotlib.legend.Legend at 0x1cdf47da940>
```



In [49]:

```
percent1=57/(780+57)
print(percent1)
percent2=39/(698+39)
print(percent2)
```

```
0.06810035842293907
0.052917232021709636
```

hence about 6.8 % of the subjects formerly smoking had a heart attack while 5.3% of the subjects who currently smoke have had a heart attack.

we could interpret that second hand smoking does seem to be much of a relevant factor in determining heart attack chances

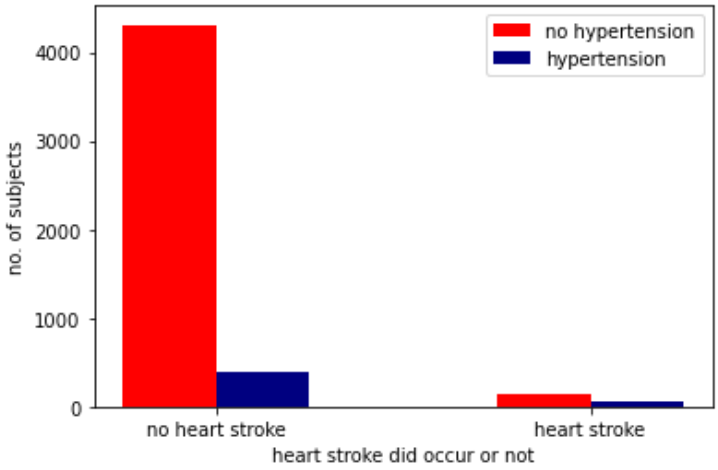
In [50]:

```
print(df_ht)
t=(df['hypertension']==1).value_counts()
print(t)
# from the data below :
plt.bar(('no heart stroke','heart stroke'),list(df_ht.iloc[0,:].values),-0.25,color='red'
,align='edge',label='no hypertension')
plt.bar(('no heart stroke','heart stroke'),list(df_ht.iloc[1,:].values),0.25,color='navy'
,align='edge',label='hypertension')
plt.xlabel('heart stroke did occur or not')
plt.ylabel('no. of subjects')
plt.legend()
```

```
stroke             0    1
hypertension
0               4309  149
1                391   60
False    4458
True      451
Name: hypertension, dtype: int64
```

Out[50]:

```
<matplotlib.legend.Legend at 0x1cdf483bc10>
```



In [51]:

```
percent2=(149/4309)*100
percent=(60/451)*100
print(percent,' ',percent2)
```

```
13.303769401330376    3.4578788582037596
```

13.303769401330376 % people suffering from hyperrtension did have a heart stroke showing high likely hood of it related to strokes compared to 3.4578788582037596 % of people suffering from heart stroke while not suffering from hyper tension

In [52]:

```
df1
```

Out[52]:

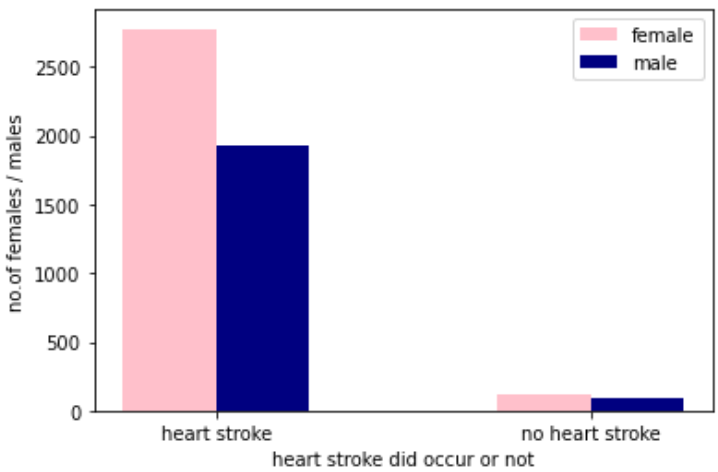
gender	Female	Male	Other
stroke			
0	2777.0	1922.0	1.0
1	120.0	89.0	NaN

In [53]:

```
plt.bar(('heart stroke','no heart stroke'),list(df1.iloc[:,0].values),-0.25,color='pink',
align='edge',label='female')
plt.bar(('heart stroke','no heart stroke'),list(df1.iloc[:,1].values),0.25,color='navy',a
lign='edge',label='male')
plt.xlabel('heart stroke did occur or not')
plt.ylabel('no.of females / males')
plt.legend()
```

Out[53]:

```
<matplotlib.legend.Legend at 0x1cdf489cee0>
```



we could conclude hence that females are more likely to suffer with an heart attack compared to males.

others wasnt considered in this data as only 1 of the category was present , who hadnt suffered a heart attack.

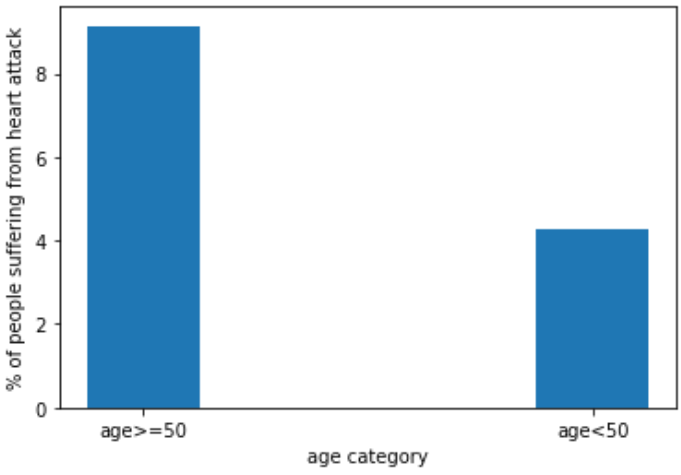
In [54]:

```
df_ab60=df[df['age']>=50]
c1=df_ab60.stroke.value_counts()
print(c1)
df_l60=df[df['stroke']<50]
c2=df_l60.stroke.value_counts()
print(c2)
percent1=(191/(1899+191))*100
percent2=(209/(209+4700))*100
print(percent1,' ',percent2)
plt.bar(['age>=50','age<50'],[percent1,percent2],0.25)
plt.ylabel('% of people suffering from heart attack')
plt.xlabel('age category')
```

```
0    1899
1     191
Name: stroke, dtype: int64
0    4700
1     209
Name: stroke, dtype: int64
9.138755980861243   4.257486249745366
```

Out[54]:

```
Text(0.5, 0, 'age category')
```



this implies a higher percentage of the older population suffer from a stroke. while about 4.25 % of people under age 50 suffer heart attack about 9.14% of older people suffer from it about a 5% increase

In [55]:

```
lst=[]
dtc = DecisionTreeClassifier(random_state=0)
x=(df2.iloc[:,[0,1,2,3,4,5,7,8,9,10,11,12,13,14,15,16]].values)
y=df2.iloc[:,5].values.reshape(-1,1)
y
```

Out[55]:

```
array([[1],
       [1],
       [1],
       ...,
       [0],
       [0],
       [0]], dtype=int64)
```

In [56]:

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25,random_state=0)
print(x_train)
```

```
[[68.  0.  0. ...  0.  1.  0.]
 [67.  1.  1. ...  0.  1.  0.]
 [82.  0.  1. ...  0.  0.  1.]
 ...
 [24.  1.  0. ...  0.  0.  1.]
 [ 9.  0.  0. ...  0.  0.  0.]
 [58.  0.  0. ...  0.  1.  0.]]
```

In [57]:

```
dtc.fit(x_train,y_train)
```

Out[57]:

```
DecisionTreeClassifier(random_state=0)
```

In [58]:

```
y_pred=dtc.predict(x_test)
```

In [59]:

```
y_pred
```

Out[59]:

```
array([0, 0, 0, ..., 0, 0, 0], dtype=int64)
```

In [60]:

```
y_test
```

Out[60]:

```
array([[0],
       [0],
       [0],
       ...,
       [0],
       [0],
       [0]], dtype=int64)
```

In [61]:

```
accuracy_score(y_test,y_pred)
lst.append(accuracy_score(y_test,y_pred)*100)
```

In [62]:

```
log=LogisticRegression()
log.fit(x_train,y_train.ravel())
y_pred2=log.predict(x_test)
print(y_test)
print(y_pred2)
accuracy_score(y_test,y_pred2)
lst.append(accuracy_score(y_test,y_pred2)*100)
```

```
[[0]
 [0]
 [0]
 ...
 [0]
 [0]
 [0]]
[0 0 0 ... 0 0 0]
```

```
C:\Users\swast\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:762: Converg
enceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

```
Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

In [ ]:

```
```

In [63]:

```
rfc=RandomForestClassifier(random_state=0)
svc=SVC(kernel='rbf',random_state=0)
```

In [64]:

```
rfc.fit(x_train,y_train.ravel())
svc.fit(x_train,y_train.ravel())
```

Out[64]:

```
SVC(random_state=0)
```

In [65]:

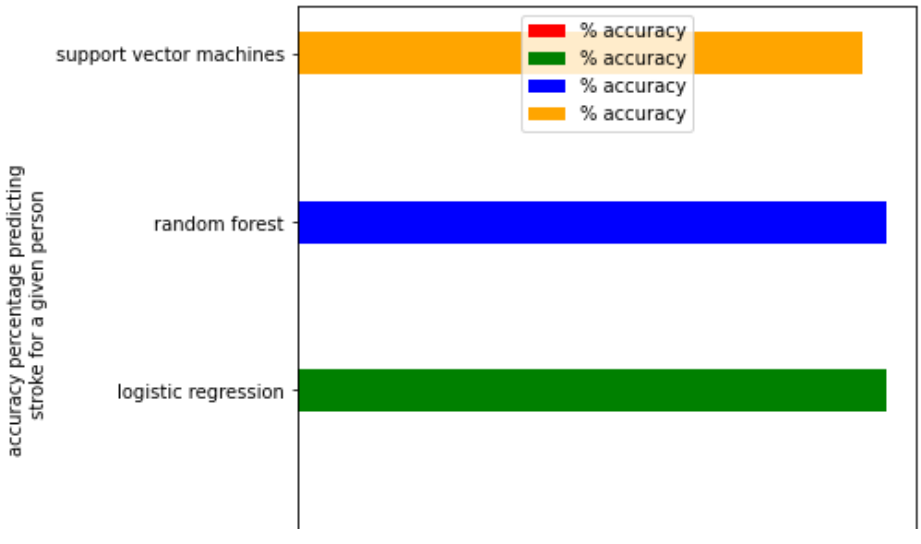
```
print(rfc.score(x_test,y_test))
lst.append(rfc.score(x_test,y_test)*100)
y_pred3=svc.predict(x_test)
print(accuracy_score(y_test,y_pred3))
lst.append(accuracy_score(y_test,y_pred3)*100)
```

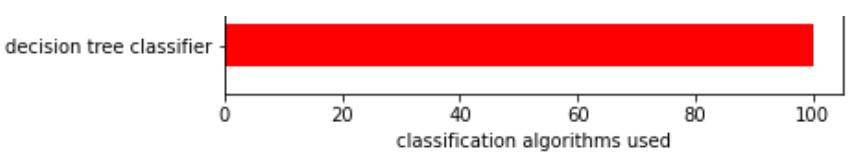
```
1.0
0.9600977198697068
```

In [66]:

```
algorithms_used= ['decision tree classifier','logistic regression','random forest','suppo
rt vector machines']
labels=list(algorithms_used)
print(list(lst))
colors = ['red', 'green', 'blue', 'orange']
plt.subplots(figsize=(6,6))
i=0
while i<=3:
    plt.barh(labels[i],lst[i],0.25,align='center',color=colors[i],label='% accuracy')
    i=i+1
plt.legend(loc='upper center')
plt.xlabel('classification algorithms used')
plt.ylabel('accuracy percentage predicting \n stroke for a given person')
plt.show()
```

```
[100.0, 100.0, 100.0, 96.00977198697068]
```




decision tree classifier
0
20
40
60
80
100
classification algorithms used

In [ ]: