```python
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        import warnings
        warnings.filterwarnings('ignore')
```

```python
In [2]: num=pd.read_csv('healthcare-dataset-stroke-data.csv',encoding='latin1')
        num
```

Out[2]:

	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
...	...	...	...	...	...	...	...	...	...	...	...	...
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

5110 rows × 12 columns

```python
In [3]: num.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
```

```python
In [4]: num.describe()
```

Out[4]:

	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

```python
In [5]: num.isnull().sum()
```

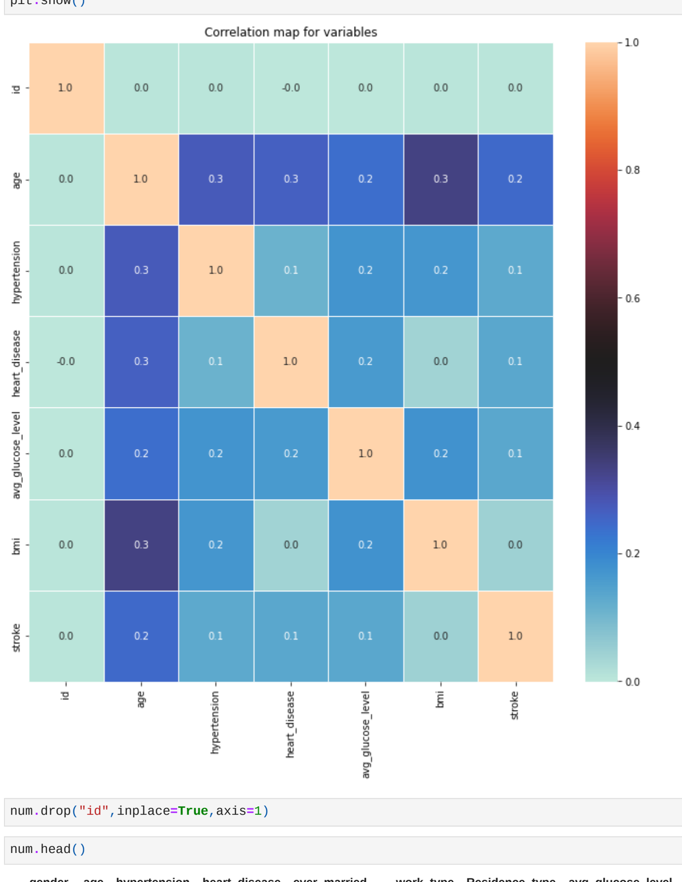
```
Out[5]:
id                     0
gender                 0
age                    0
hypertension           0
heart_disease          0
ever_married           0
work_type              0
Residence_type         0
avg_glucose_level      0
bmi                  201
smoking_status         0
stroke       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

```python
In [6]: num.corr()
```

Out[6]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	stroke
id	1.000000	0.003538	0.003550	-0.001296	0.001092	0.003084	0.006388
age	0.003538	1.000000	0.276398	0.263796	0.238171	0.333398	0.245257
hypertension	0.003550	0.276398	1.000000	0.108306	0.174474	0.167811	0.127904
heart_disease	-0.001296	0.263796	0.108306	1.000000	0.161857	0.041357	0.134914
avg_glucose_level	0.001092	0.238171	0.174474	0.161857	1.000000	0.175502	0.131945
bmi	0.003084	0.333398	0.167811	0.041357	0.175502	1.000000	0.042374
stroke	0.006388	0.245257	0.127904	0.134914	0.131945	0.042374	1.000000

```python
In [7]: f,ax = plt.subplots(figsize=(12, 12))
        ax.set_title('Correlation map for variables')
        sns.heatmap(num.corr(), annot=True, linewidths=.5, fmt= '.1f',ax=ax,cmap="icefire")
        plt.show()
```




```python
In [8]: num.drop("id",inplace=True,axis=1)
```

```python
In [9]: num.head()
```

Out[9]:

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

```python
In [10]: num.nunique()
```

```
Out[10]:
gender                  3
age                   104
hypertension            2
heart_disease           2
ever_married            2
work_type               5
Residence_type          2
avg_glucose_level    3979
bmi                   418
smoking_status          4
stroke                  2
dtype: int64
```

```python
In [11]: num.dtypes
```

```
Out[11]:
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
```

```python
In [12]: num=num.fillna(num['bmi'].mean())
```

```python
In [13]: num.head()
```

Out[13]:

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	Male	67.0	0	1	Yes	Private	Urban	228.69	36.600000	formerly smoked	1
1	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	28.893237	never smoked	1
2	Male	80.0	0	1	Yes	Private	Rural	105.92	32.500000	never smoked	1
3	Female	49.0	0	0	Yes	Private	Urban	171.23	34.400000	smokes	1
4	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.000000	never smoked	1

```python
In [14]: num.isnull().sum()
```

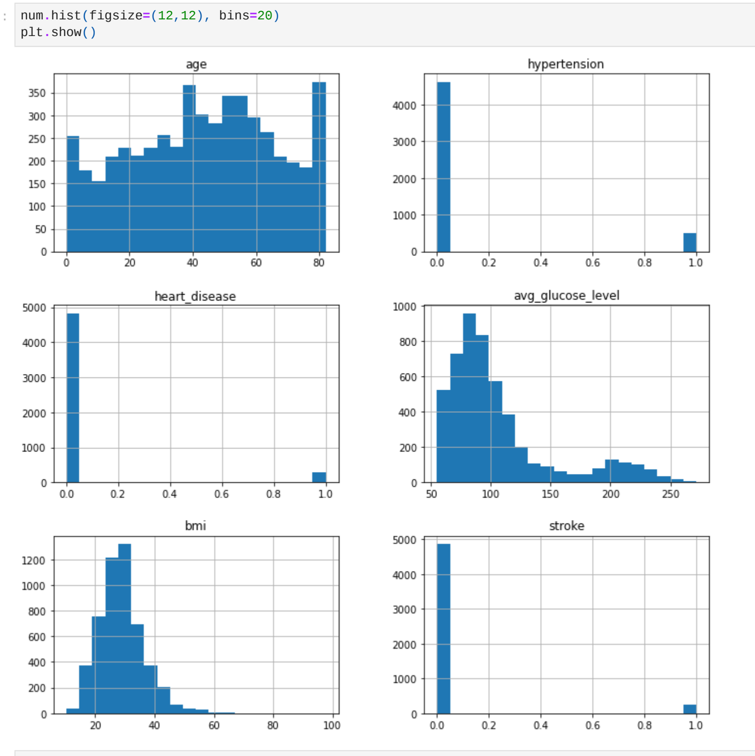
```
Out[14]:
gender               0
age                  0
hypertension         0
heart_disease        0
ever_married         0
work_type            0
Residence_type       0
avg_glucose_level    0
bmi                  0
smoking_status       0
stroke               0
dtype: int64
```

```python
In [15]: num['gender'].value_counts()
```

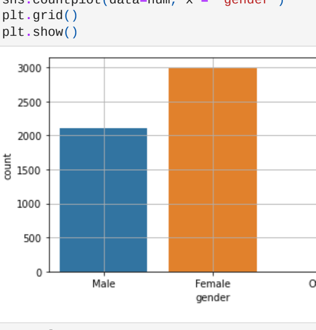
```
Out[15]:
Female    2994
Male      2115
Other        1
Name: gender, dtype: int64
```

Data visualization

```python
In [16]: num.hist(figsize=(12,12), bins=20)
         plt.show()
```



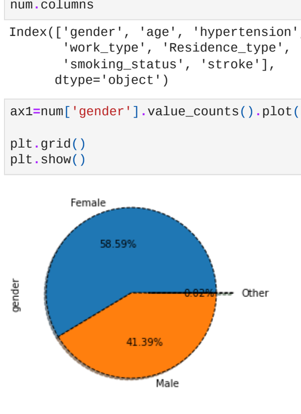

```python
In [17]: sns.countplot(data=num, x = 'gender')
         plt.grid()
         plt.show()
```



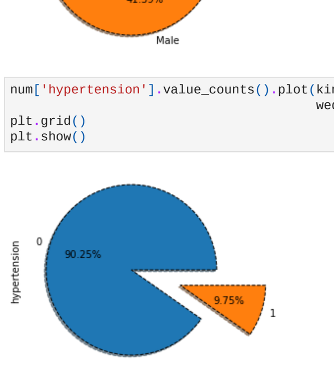

```python
In [18]: num.columns
```

```
Out[18]: Index(['gender', 'age', 'hypertension', 'heart_disease', 'ever_married',
       'work_type', 'Residence_type', 'avg_glucose_level', 'bmi',
       'smoking_status', 'stroke'],
      dtype='object')
```

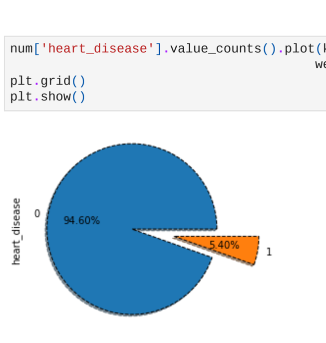
```python
In [19]: ax1=num['gender'].value_counts().plot(kind='pie',autopct='%0.2f%%',explode=[0,0,0.2],
                                          wedgeprops={'edgecolor':'k','ls':'--'},shadow=True)
         plt.grid()
         plt.show()
```



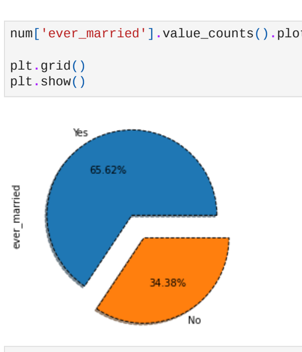

```python
In [20]: num['hypertension'].value_counts().plot(kind='pie',autopct='%0.2f%%',explode=[0,0.6],
                                          wedgeprops={'edgecolor':'k','ls':'--'},shadow=True)
         plt.grid()
         plt.show()
```



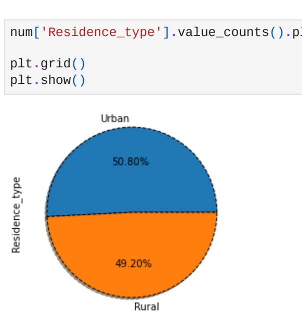

```python
In [21]: num['heart_disease'].value_counts().plot(kind='pie',autopct='%0.2f%%',explode=[0,0.5],
                                          wedgeprops={'edgecolor':'k','ls':'--'},shadow=True)
         plt.grid()
         plt.show()
```



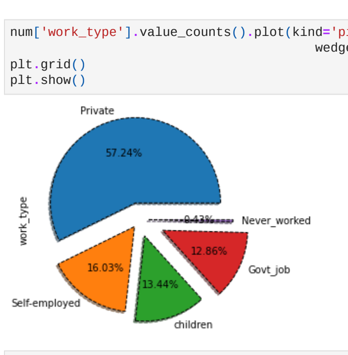

```python
In [22]: num['ever_married'].value_counts().plot(kind='pie',autopct='%0.2f%%',explode=[0,0.3],
                                          wedgeprops={'edgecolor':'k','ls':'--'},shadow=True)
         plt.grid()
         plt.show()
```



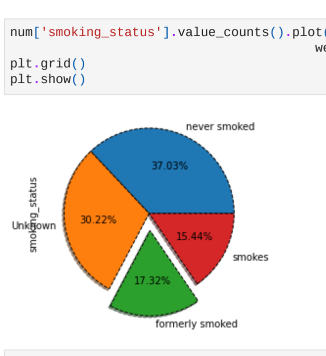

```python
In [23]: num['Residence_type'].value_counts().plot(kind='pie',autopct='%0.2f%%',explode=[0,0],
                                          wedgeprops={'edgecolor':'k','ls':'--'},shadow=True)
         plt.grid()
         plt.show()
```



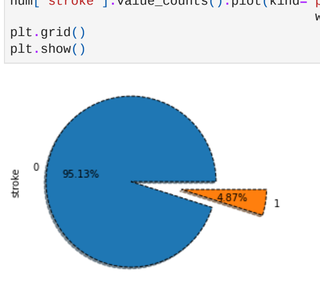

```python
In [24]: num['work_type'].value_counts().plot(kind='pie',autopct='%0.2f%%',explode=[0.2,0.1,0.2,0.3,0.1],
                                          wedgeprops={'edgecolor':'k','ls':'--'},shadow=True)
         plt.grid()
         plt.show()
```




```python
In [25]: num['smoking_status'].value_counts().plot(kind='pie',autopct='%0.2f%%',explode=[0,0,0.2,0],
                                          wedgeprops={'edgecolor':'k','ls':'--'},shadow=True)
         plt.grid()
         plt.show()
```




```python
In [26]: num['stroke'].value_counts().plot(kind='pie',autopct='%0.2f%%',explode=[0,0.6],
                                          wedgeprops={'edgecolor':'k','ls':'--'},shadow=True)
         plt.grid()
         plt.show()
```



Data preprocessing

```python
In [27]: from sklearn.preprocessing import LabelEncoder,StandardScaler
```

```python
In [28]: ss=StandardScaler()
         LE=LabelEncoder()
```

```python
In [29]: num['gender'] = LE.fit_transform(num['gender'])
```

```python
In [30]: num['ever_married']=LE.fit_transform(num['ever_married'])
```

```python
In [31]: num['work_type']=LE.fit_transform(num['work_type'])
```

```python
In [32]: num['Residence_type']=LE.fit_transform(num['Residence_type'])
```

```python
In [33]: num['smoking_status']=LE.fit_transform(num['smoking_status'])
```

```python
In [34]: num.head()
```

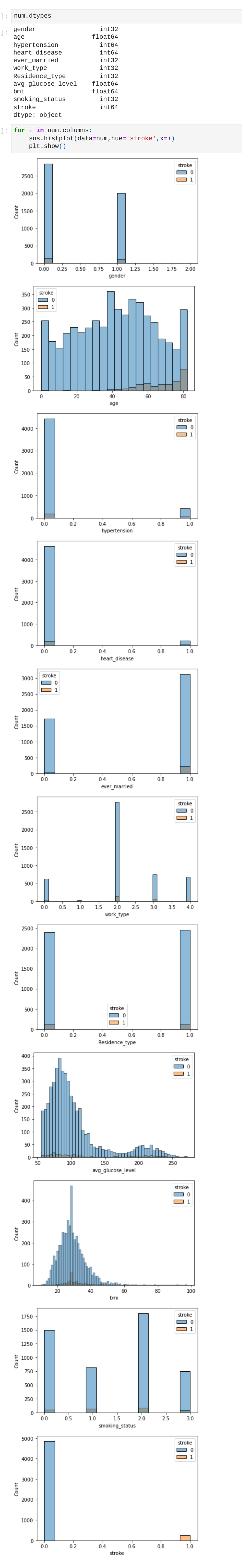
Out[34]:

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	1	67.0	0	1	1	2	1	228.69	36.600000	1	1
1	0	61.0	0	0	1	3	0	202.21	28.893237	2	1
2	1	80.0	0	1	1	2	0	105.92	32.500000	2	1
3	0	49.0	0	0	1	2	1	171.23	34.400000	3	1
4	0	79.0	1	0	1	3	0	174.12	24.000000	2	1

```python
In [35]: num.dtypes
```

```
Out[35]:
gender                 int32
age                  float64
hypertension           int64
heart_disease          int64
ever_married           int32
work_type              int32
Residence_type         int32
avg_glucose_level    float64
bmi                  float64
smoking_status         int32
stroke                 int64
dtype: object
```

```python
In [36]: for i in num.columns:
             sns.histplot(data=num,hue='stroke',x=i)
             plt.show()
```



Dataset spliting

```python
In [37]: X = num.drop(['stroke'], axis=1)
         y = num['stroke']
```

```python
In [38]: from sklearn.model_selection import train_test_split
         X_train, X_test , y_train , y_test = train_test_split(X,y,test_size=0.2,random_state=0)
```

```python
In [39]: print('X_train:', X_train.shape)
         print('y_train:', y_train.shape)
         print('X_test:', X_test.shape)
         print('y_test:', y_test.shape)
```

```
X_train: (4088, 10)
y_train: (4088,)
X_test: (1022, 10)
y_test: (1022,)
```

```python
In [40]: from sklearn.linear_model import Lasso
```

```python
In [41]: l1=Lasso(alpha=0.001)
```

```python
In [42]: l1.fit(X_train,y_train)
```

```
Out[42]: Lasso(alpha=0.001)
```

```python
In [43]: l1.predict(X_test)
```

```
Out[43]: array([ 0.1952547 , -0.01463052,  0.06736623, ...,  0.07707162,
        0.16620552,  0.01093787])
```

```python
In [44]: l1.score(X_train,y_train)
```

```
Out[44]: 0.08272715223530969
```

RandomForestClassifier

```python
In [45]: from sklearn.ensemble import RandomForestClassifier
```

```python
In [46]: Rfc = RandomForestClassifier(n_jobs=2, random_state=0)
```

```python
In [47]: Rfc.fit(X_train, y_train)
```

```
Out[47]: RandomForestClassifier(n_jobs=2, random_state=0)
```

```python
In [48]: y_pred = Rfc.predict(X_test)
```

```python
In [49]: acc_rf = round(Rfc.score(X_test,y_test) * 100, 2)
```

```python
In [50]: from sklearn import metrics #FOR ACCURACY CALCULATION
```

```python
In [51]: print("Random Forest Classifier Accuracy:",metrics.accuracy_score(y_test, y_pred)*100,"%")
```

```
Random Forest Classifier Accuracy: 94.6183953033268 %
```

KNeighborsClassifier

```python
In [52]: #TESTING USING KNEIGHBORS CLASSIFIERS
         from sklearn.neighbors import KNeighborsClassifier
         knC = KNeighborsClassifier(n_neighbors=3)
```

```python
In [53]: knC.fit(X_train, y_train)
```

```
Out[53]: KNeighborsClassifier(n_neighbors=3)
```

```python
In [54]: y_pred = knC.predict(X_test)
         acc_knC = round(knC.score(X_test,y_test) * 100, 2)
```

```python
In [55]: from sklearn import metrics
```

```python
In [56]: print("kNN Accuracy:",metrics.accuracy_score(y_test, y_pred)*100,"%")
```

```
kNN Accuracy: 94.03131115459882 %
```

DecisionTreeClassifier

```python
In [57]: from sklearn.tree import DecisionTreeClassifier
         from sklearn import tree
```

```python
In [58]: Dtc =DecisionTreeClassifier(max_depth=10)
```

```python
In [59]: Dtc = Dtc.fit(X_train,y_train)
```

```python
In [60]: y_pred = Dtc.predict(X_test)
         _dtc = round(Dtc.score(X_test,y_test) * 100, 2)
```

```python
In [61]: from sklearn.metrics import accuracy_score
```

```python
In [62]: print ("Decision Tree Accuracy:", metrics.accuracy_score(y_test, y_pred)*100,"%")
```

```
Decision Tree Accuracy: 93.24853228962819 %
```

The ML algorithm that perform the best was Random_Forest _Classifier with Accuracy: 94.6183953033268 %