





# Library

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix,accuracy_score,f1_score,precision_score,classification_report
from sklearn.metrics import recall_score
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.impute import SimpleImputer
from sklearn.model_selection import KFold
from sklearn.tree import DecisionTreeClassifier
```

# Membaca dataset dan menampilkan 5 baris data



	<pre>data=pd.read_csv('healthcare-dataset-stroke-data.csv') data.head()</pre>													
✓ 0.9s														
	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		



### Drop kolom id

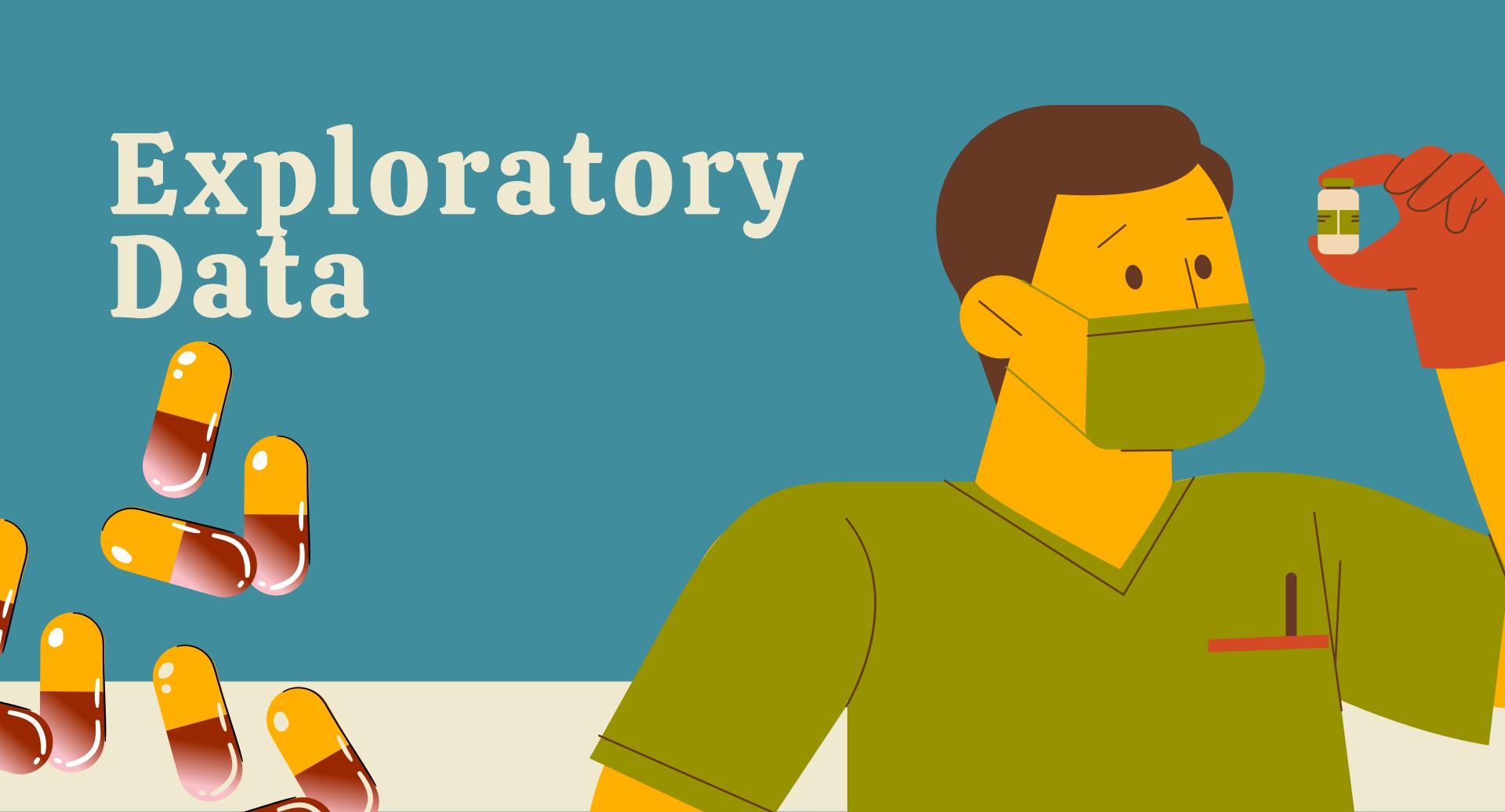


```
#Drop kolom Id karna gak guna
data = data.drop(columns=['id'])

$\square$ 0.3s
```







```
data['gender'].value_counts()
 ✓ 0.4s
Female
         2994
Male
         2115
          1
Other
Name: gender, dtype: int64
   data[data['gender'] == 'Other']
 ✓ 0.6s
          id gender age hypertension heart_disease ever_married work_type Residence_type avg_glucose_level bmi smoking_status stroke
                                                                                                   143.33 22.4 formerly smoked
 3116 56156 Other 26.0
                                    0
                                                                    Private
                                                                                    Rural
   data.drop([3116], inplace=True)
   data['gender'].value_counts()
 ✓ 0.5s
Female
         2994
         2115
Male
Name: gender, dtype: int64
```



## info(): Nomor index beserta tipe datanya.

```
data.info()
 ✓ 0.6s
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5109 entries, 0 to 5108
Data columns (total 11 columns):
                    Non-Null Count Dtype
# Column
                5109 non-null object
    gender
               5109 non-null float64
    age
   hypertension 5109 non-null
                                  int64
    heart_disease 5109 non-null
                                  int64
    ever_married 5109 non-null
                                  object
    work_type 5109 non-null
                                  object
   Residence_type 5109 non-null object
    avg_glucose_level 5109 non-null float64
    bmi
          4908 non-null float64
9 smoking_status 5109 non-null
                                  object
10 stroke
                    5109 non-null int64
dtypes: float64(3), int64(3), object(5)
memory usage: 439.2+ KB
```

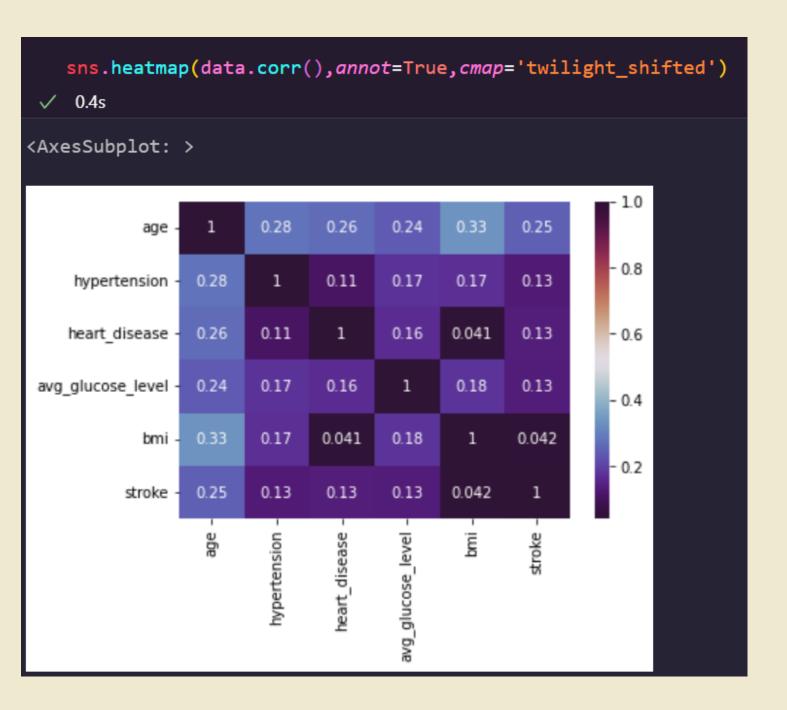
Menampilkan informasi detail tentang dataframe, seperti jumlah baris data, nama-nama kolom berserta jumlah data dan tipe datanya, dan sebagainya.

# describe()

<pre>data.describe()  </pre> <pre> <pre> </pre> <pre> </pre></pre>											
	age	hypertension	heart_disease	avg_glucose_level	bmi	stroke					
count	5109.000000	5109.000000	5109.000000	5109.000000	4908.00000	5109.000000					
mean	43.229986	0.097475	0.054022	106.140399	28.89456	0.048738					
std	22.613575	0.296633	0.226084	45.285004	7.85432	0.215340					
min	0.080000	0.000000	0.000000	55.120000	10.30000	0.000000					
25%	25.000000	0.000000	0.000000	77.240000	23.50000	0.000000					
50%	45.000000	0.000000	0.000000	91.880000	28.10000	0.000000					
75%	61.000000	0.000000	0.000000	114.090000	33.10000	0.000000					
max	82.000000	1.000000	1.000000	271.740000	97.60000	1.000000					

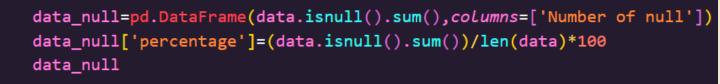
## Mengecek korelasi

data.corr() ✓ 0.4s						
	age	hypertension	heart_disease	avg_glucose_level	bmi	stroke
age	1.000000	0.276367	0.263777	0.238323	0.333314	0.245239
hypertension	0.276367	1.000000	0.108292	0.174540	0.167770	0.127891
heart_disease	0.263777	0.108292	1.000000	0.161907	0.041322	0.134905
avg_glucose_level	0.238323	0.174540	0.161907	1.000000	0.175672	0.131991
bmi	0.333314	0.167770	0.041322	0.175672	1.000000	0.042341
stroke	0.245239	0.127891	0.134905	0.131991	0.042341	1.000000





Mencari nilai null dan menghitung percentage nya

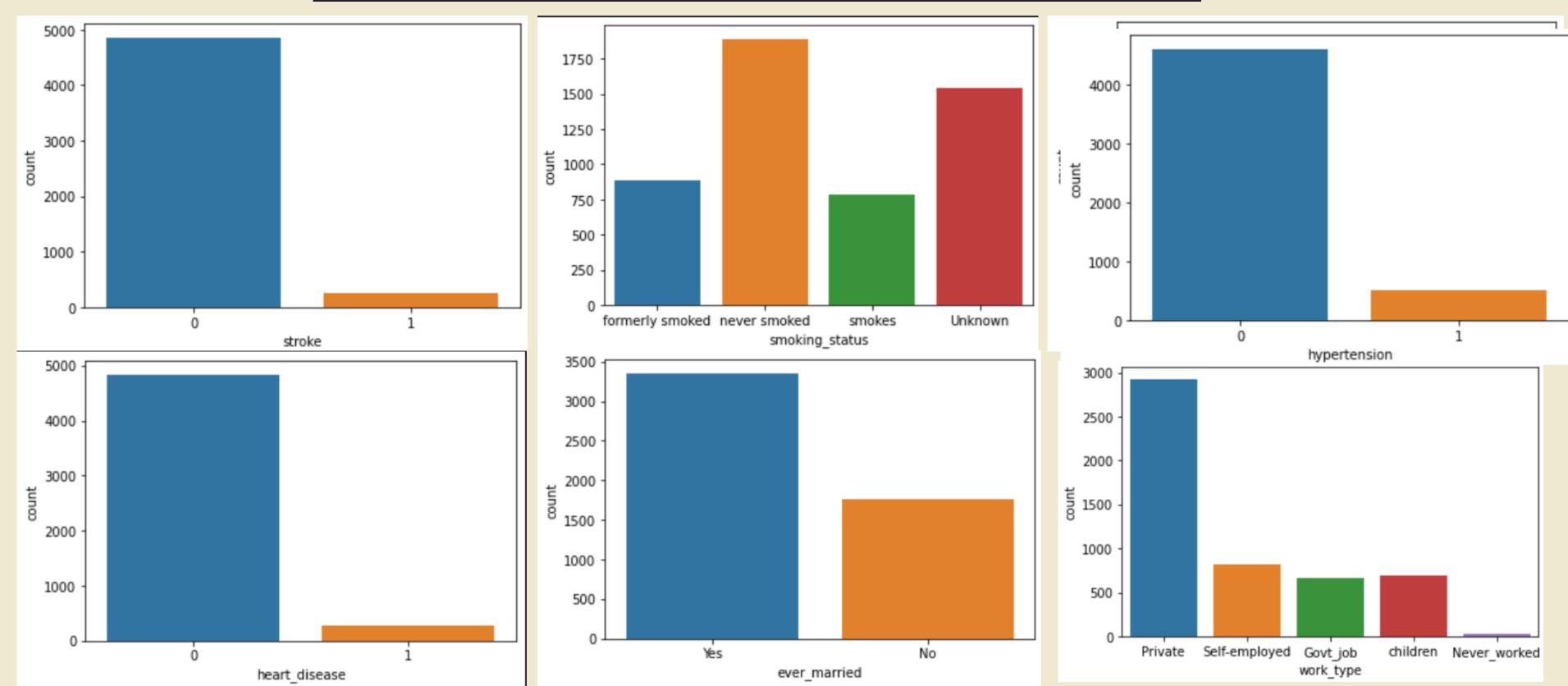


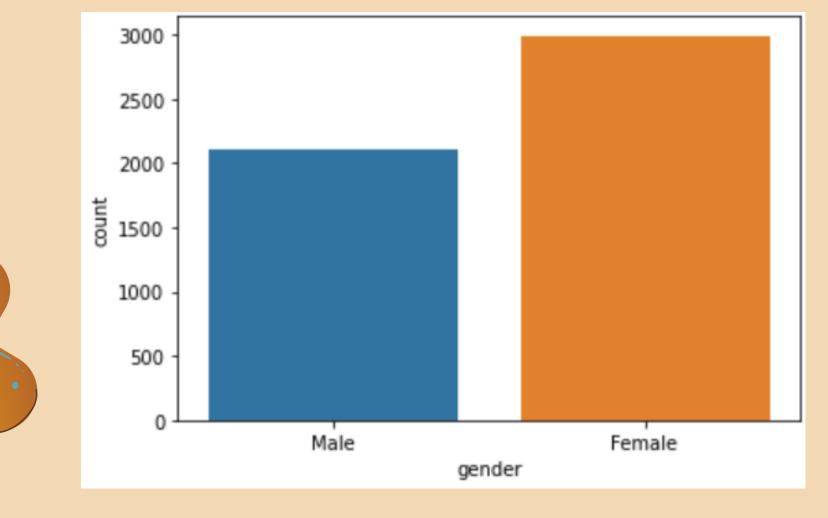
✓ 0.4s

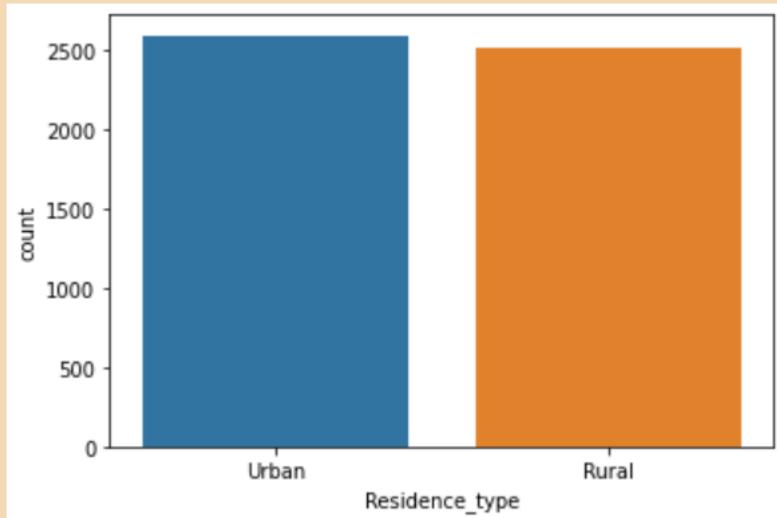
	Number of null	percentage
gender	0	0.000000
age	0	0.000000
hypertension	0	0.000000
heart_disease	0	0.000000
ever_married	0	0.000000
work_type	0	0.000000
Residence_type	0	0.000000
avg_glucose_level	0	0.000000
bmi	201	3.934234
smoking_status	0	0.000000
stroke	0	0.000000

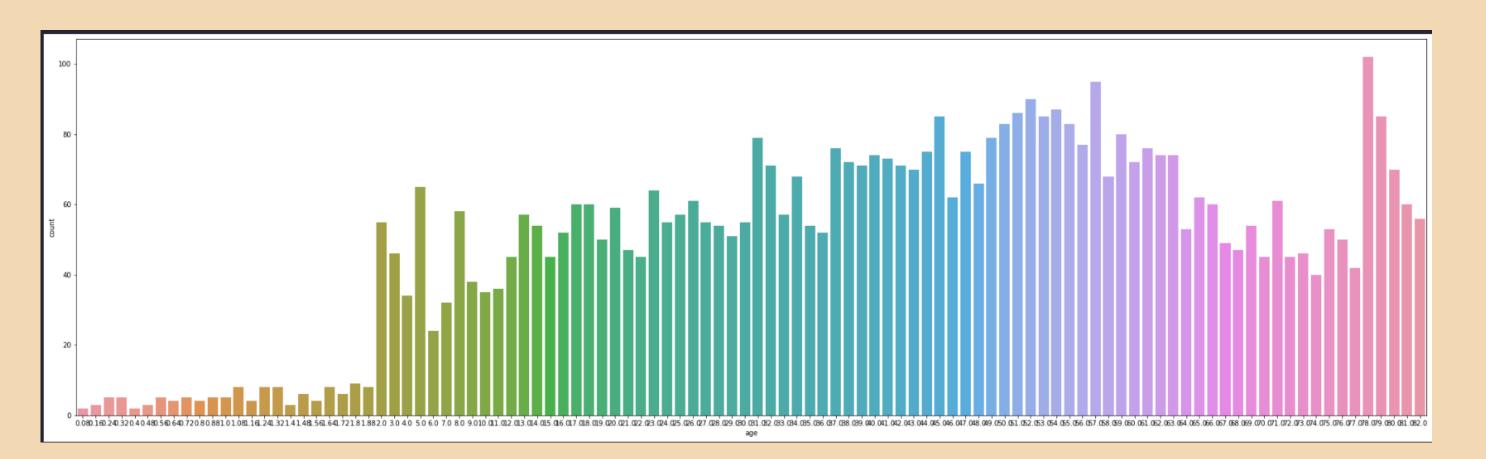
#### Tampilkan distribusi beberapa kolom

```
list1=['stroke', 'smoking_status', 'hypertension', 'heart_disease', 'ever_married', 'work_type', 'Residence_type', 'gender', 'age']
for col in list1:
    plt.figure()
    if col=='age':
        plt.figure(figsize=(35,10))
    sns.countplot(x=col, data=data)
```











```
#Membagi data Label dan feature

X=data.iloc[:,0:-1]
y=data.iloc[:,-1]
key=X.keys()

✓ 0.3s
```

X

✓ 0.4s

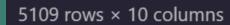
	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status
0	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked
1	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	NaN	never smoked
2	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never smoked
3	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smokes
4	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never smoked
5104	Female	80.0	1	0	Yes	Private	Urban	83.75	NaN	never smoked
5105	Female	81.0	0	0	Yes	Self-employed	Urban	125.20	40.0	never smoked
5106	Female	35.0	0	0	Yes	Self-employed	Rural	82.99	30.6	never smoked
5107	Male	51.0	0	0	Yes	Private	Rural	166.29	25.6	formerly smoked
5108	Female	44.0	0	0	Yes	Govt_job	Urban	85.28	26.2	Unknown

5109 rows × 10 columns

#### Mengubah data yang bertype objek menjadi numerik

```
list1=['gender','ever_married','work_type','Residence_type','smoking_status']
label=LabelEncoder()
for col in list1:
     X[col]=label.fit_transform(X[col])
X
     0.6s
```

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status
0	1	67.0	0	1	1	2	1	228.69	36.6	1
1	0	61.0	0	0	1	3	0	202.21	NaN	2
2	1	80.0	0	1	1	2	0	105.92	32.5	2
3	0	49.0	0	0	1	2	1	171.23	34.4	3
4	0	79.0	1	0	1	3	0	174.12	24.0	2
5104	0	80.0	1	0	1	2	1	83.75	NaN	2
5105	0	81.0	0	0	1	3	1	125.20	40.0	2
5106	0	35.0	0	0	1	3	0	82.99	30.6	2
5107	1	51.0	0	0	1	2	0	166.29	25.6	1
5108	0	44.0	0	0	1	0	1	85.28	26.2	0





#### Mengganti nilai NaN

```
impute = SimpleImputer(missing_values=np.nan, strategy='mean')
   X = impute.fit_transform(X)
   pd.DataFrame(X,coLumns=key)
 ✓ 0.6s
       gender age hypertension heart_disease ever_married work_type Residence_type avg_glucose_level bmi smoking_status
          1.0 67.0
                             0.0
                                           1.0
                                                        1.0
                                                                   2.0
                                                                                  1.0
                                                                                                228.69 36.60000
                                                                                                                            1.0
          0.0 61.0
                                                                                                202.21 28.89456
                             0.0
                                          0.0
                                                        1.0
                                                                   3.0
                                                                                  0.0
                                                                                                                            2.0
    2
          1.0 80.0
                             0.0
                                           1.0
                                                        1.0
                                                                   2.0
                                                                                  0.0
                                                                                                 105.92 32.50000
                                                                                                                            2.0
                                                                                                171.23 34.40000
                             0.0
    3
          0.0 49.0
                                          0.0
                                                        1.0
                                                                   2.0
                                                                                  1.0
                                                                                                                            3.0
                                                                                                 174.12 24.00000
          0.0 79.0
                             1.0
                                          0.0
                                                        1.0
                                                                   3.0
                                                                                  0.0
                                                                                                                            2.0
 5104
          0.0 80.0
                             1.0
                                          0.0
                                                        1.0
                                                                   2.0
                                                                                  1.0
                                                                                                 83.75 28.89456
                                                                                                                            2.0
5105
          0.0 81.0
                             0.0
                                          0.0
                                                        1.0
                                                                   3.0
                                                                                  1.0
                                                                                                 125.20 40.00000
                                                                                                                            2.0
5106
          0.0 35.0
                             0.0
                                          0.0
                                                        1.0
                                                                   3.0
                                                                                  0.0
                                                                                                 82.99 30.60000
                                                                                                                            2.0
5107
          1.0 51.0
                             0.0
                                          0.0
                                                        1.0
                                                                   2.0
                                                                                  0.0
                                                                                                 166.29 25.60000
                                                                                                                            1.0
5108
          0.0 44.0
                             0.0
                                          0.0
                                                        1.0
                                                                   0.0
                                                                                  1.0
                                                                                                 85.28 26.20000
                                                                                                                            0.0
5109 rows × 10 columns
```



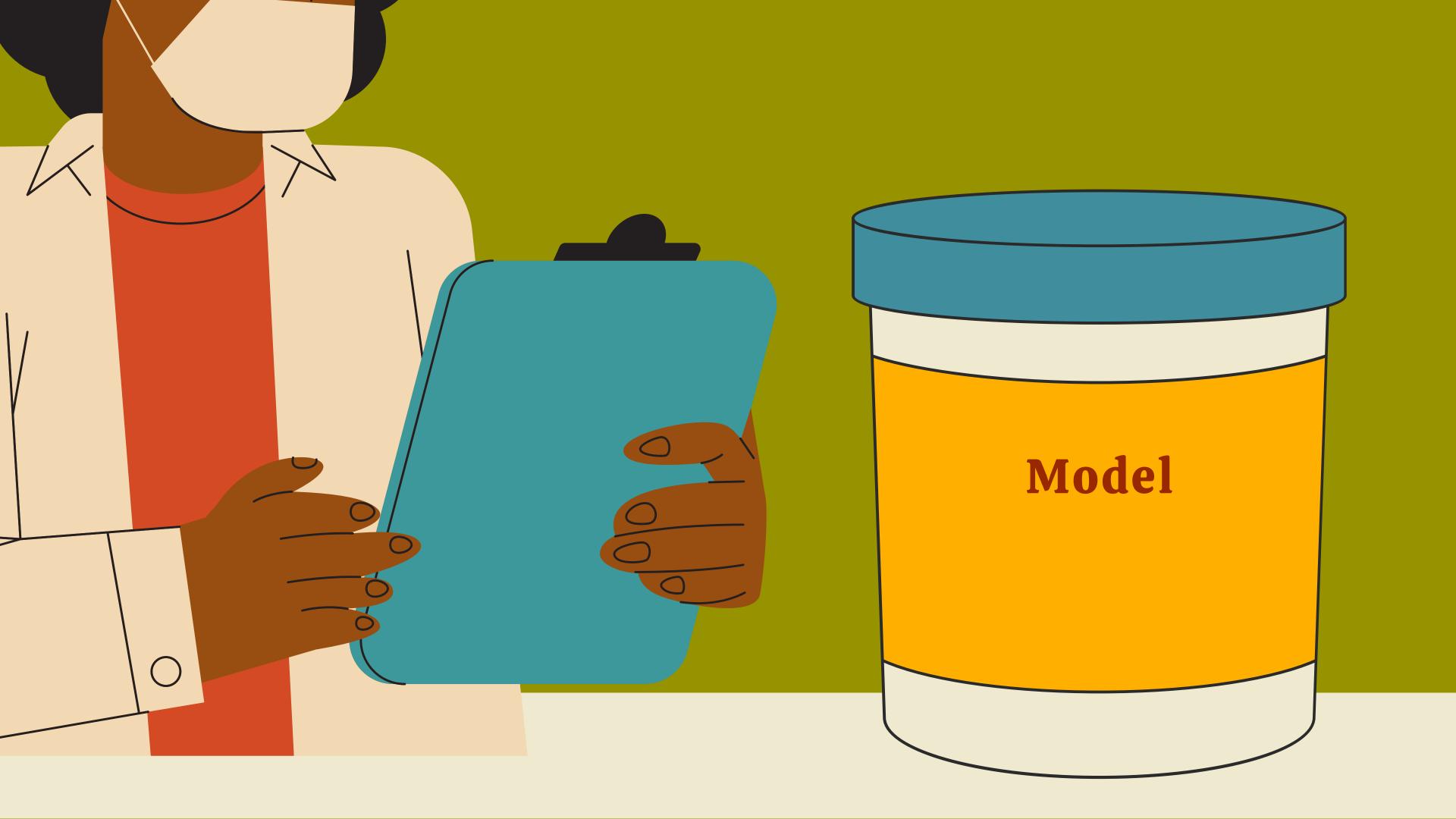
#### MinMaxScaler

scaler = MinMaxScaler(copy=True, feature\_range=(0, 1))
X = scaler.fit\_transform(X)
pd.DataFrame(X,columns=key)

✓ 0.5s

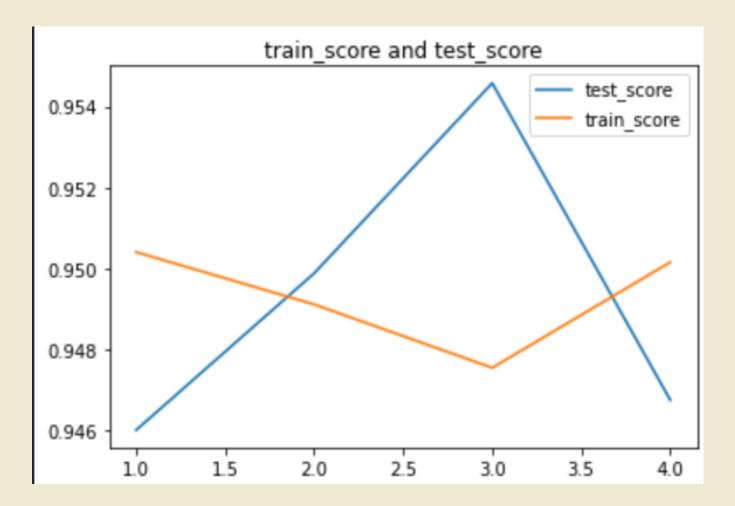
	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status
0	1.0	0.816895	0.0	1.0	1.0	0.50	1.0	0.801265	0.301260	0.333333
1	0.0	0.743652	0.0	0.0	1.0	0.75	0.0	0.679023	0.212996	0.666667
2	1.0	0.975586	0.0	1.0	1.0	0.50	0.0	0.234512	0.254296	0.666667
3	0.0	0.597168	0.0	0.0	1.0	0.50	1.0	0.536008	0.276060	1.000000
4	0.0	0.963379	1.0	0.0	1.0	0.75	0.0	0.549349	0.156930	0.666667
5104	0.0	0.975586	1.0	0.0	1.0	0.50	1.0	0.132167	0.212996	0.666667
5105	0.0	0.987793	0.0	0.0	1.0	0.75	1.0	0.323516	0.340206	0.666667
5106	0.0	0.426270	0.0	0.0	1.0	0.75	0.0	0.128658	0.232532	0.666667
5107	1.0	0.621582	0.0	0.0	1.0	0.50	0.0	0.513203	0.175258	0.333333
5108	0.0	0.536133	0.0	0.0	1.0	0.00	1.0	0.139230	0.182131	0.000000
5109 rows × 10 columns										





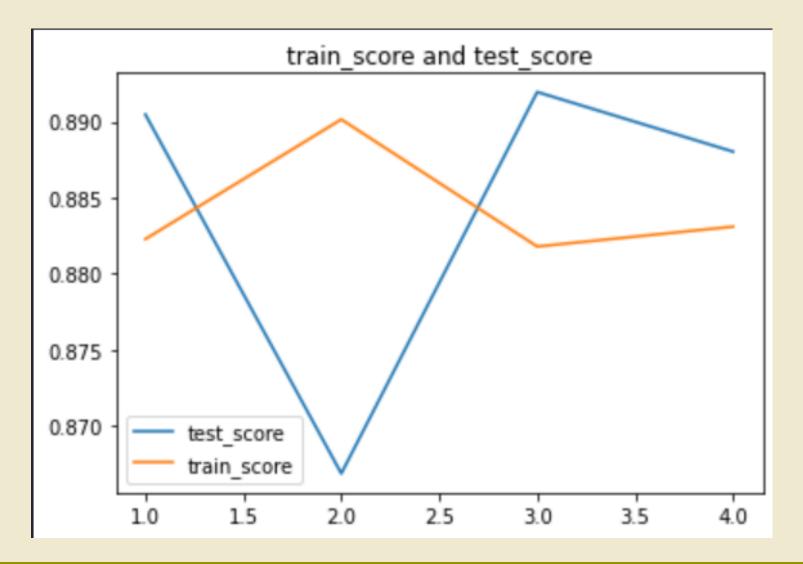
#### Menggunakan Model RandomForeestClassifier

```
kfold = KFold(n_splits=4, random_state=44, shuffle =True)
   test_score=[]
   train_score=[]
   RandomForestClassifierModel = RandomForestClassifier(criterion = 'gini',n_estimators=100,max_depth=25,random_state=33)
   for train_index, test_index in kfold.split(X):
       X_train, X_test = X[train_index], X[test_index]
       y_train, y_test = y[train_index], y[test_index]
       RandomForestClassifierModel.fit(X[:1350], y[:1350])
       test_score.append(RandomForestClassifierModel.score(X_test, y_test))
       train_score.append(RandomForestClassifierModel.score(X_train, y_train))
   plt.plot(range(1,5),test_score, label="test_score")
   plt.plot(range(1,5),train_score,label="train_score")
   plt.title("train_score and test_score")
   plt.legend()
   print("test score =",np.mean(test_score))
   print("train score", np.mean(train_score))
 ✓ 1.6s
test score = 0.9493057929934081
train score 0.9493052195064
```



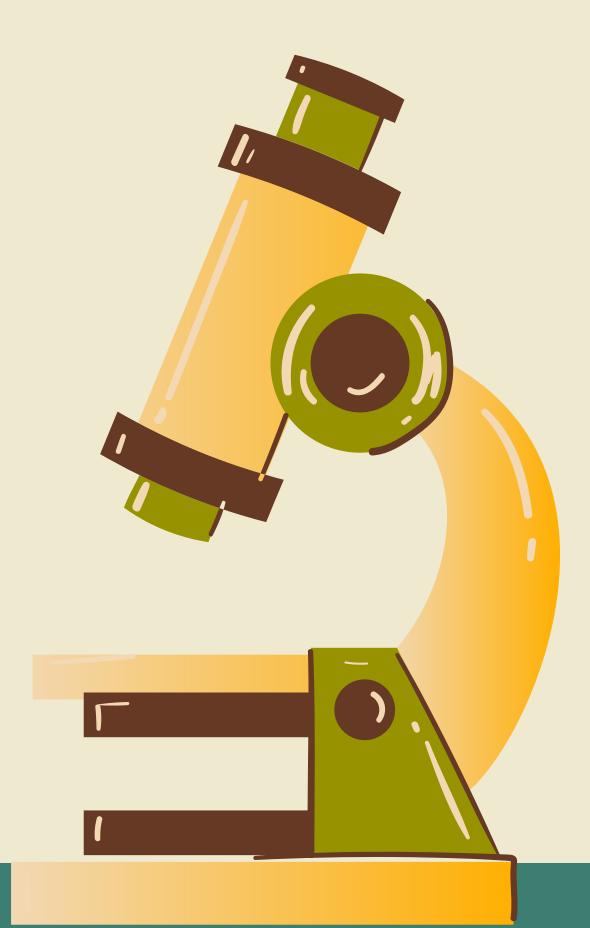
#### Menggunakan Model DecisionTreeClassifier

```
DecisionTreeClassifierModel = DecisionTreeClassifier(criterion='gini',max_depth=10,random_state=33)
   test_score=[]
   train_score=[]
   for train_index, test_index in kfold.split(X):
       X_train, X_test = X[train_index], X[test_index]
       y_train, y_test = y[train_index], y[test_index]
       DecisionTreeClassifierModel.fit(X[:1350], y[:1350])
       test_score.append(DecisionTreeClassifierModel.score(X_test, y_test))
       train_score.append(DecisionTreeClassifierModel.score(X_train, y_train))
   plt.plot(range(1,5),test_score, label="test_score")
   plt.plot(range(1,5),train_score, label="train_score")
   plt.title("train_score and test_score")
   plt.legend()
   print("test score =",np.mean(test_score))
   print("train score", np.mean(train_score))
 ✓ 0.2s
test score = 0.8843205846056938
train score 0.8843216516289211
```



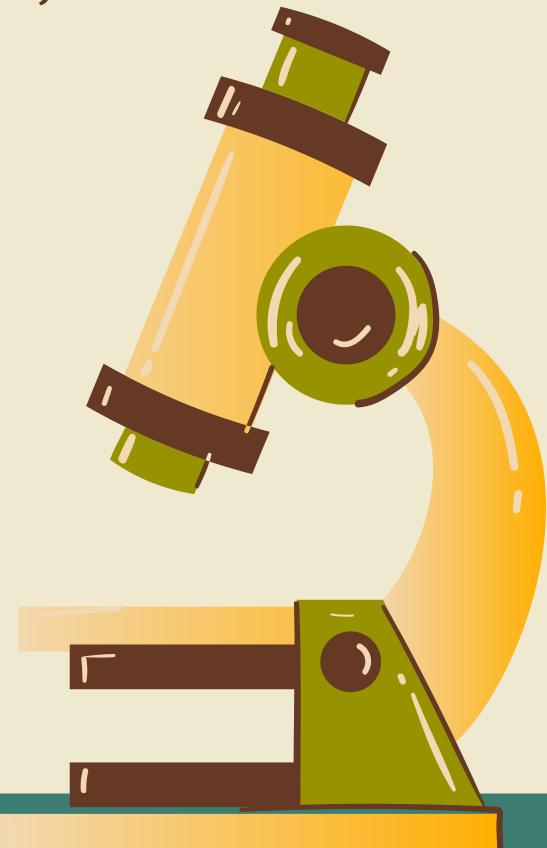
#### **Confusion Matrix**





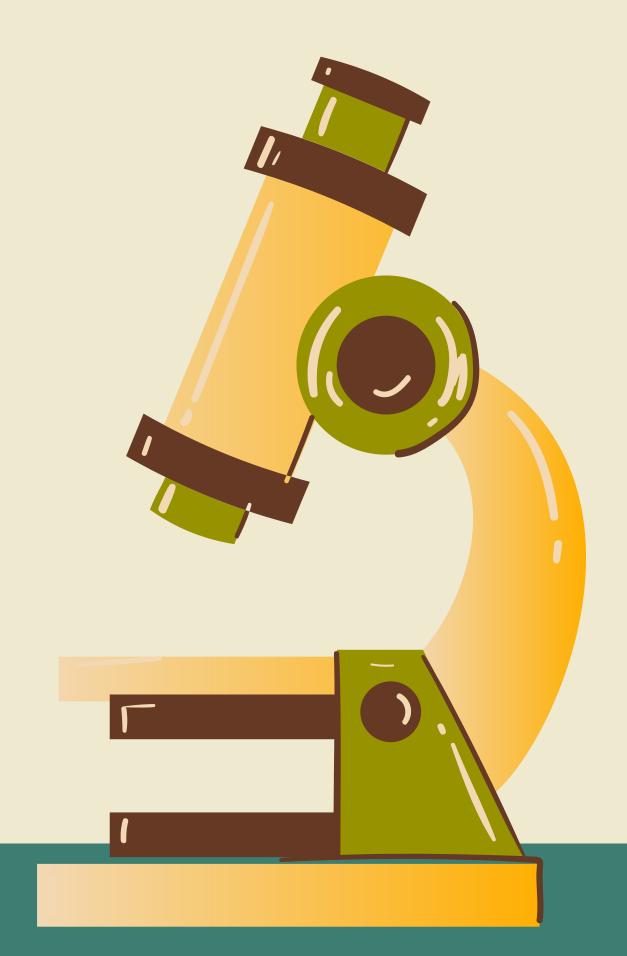
Menghitun Accuracy, Precision, Recall, dan F1-Score

```
print('Accuracy: {}'.format(accuracy_score(y, y_pred)))
 ✓ 0.4s
Accuracy: 0.9493051477784302
   print('Precision: {}'.format(precision_score(y, y_pred)))
 ✓ 0.6s
Precision: 0.49015748031496065
   print('Recall: {}'.format(recall_score(y, y_pred)))
 ✓ 0.4s
Recall: 1.0
   print('F1-Score: {}'.format(f1_score(y, y_pred))) ?
 ✓ 0.3s
F1-Score: 0.6578599735799208
```



#### **Classification Report**

```
ClassificationReport = classification_report(y,y_pred)
   print(ClassificationReport )
 ✓ 0.5s
              precision
                           recall f1-score
                                              support
           0
                   1.00
                             0.95
                                       0.97
                                                 4860
                   0.49
                             1.00
                                                  249
                                       0.66
                                       0.95
                                                 5109
    accuracy
                             0.97
                                       0.82
                                                 5109
                   0.75
  macro avg
weighted avg
                             0.95
                                       0.96
                   0.98
                                                 5109
```



# Thank you for listening!



Don't hesitate to ask any questions!