```
import pandas as pd
import numpy as np

data=pd.read_csv("diabetes.csv")
```

data

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigr
0	6	148	72	35	0	33.6	
1	1	85	66	29	0	26.6	
2	8	183	64	0	0	23.3	
3	1	89	66	23	94	28.1	
4	0	137	40	35	168	43.1	
763	10	101	76	48	180	32.9	
764	2	122	70	27	0	36.8	
765	5	121	72	23	112	26.2	
766	1	126	60	0	0	30.1	
767	1	93	70	31	0	30.4	
768 rc	768 rows × 9 columns						>

data.isnull().any()

```
Pregnancies
                            False
Glucose
                            False
BloodPressure
                            False
SkinThickness
                            False
Insulin
                            False
BMI
                           False
DiabetesPedigreeFunction
                           False
Age
                           False
Outcome
                            False
dtype: bool
```

data.isna().sum()

```
Pregnancies 0
Glucose 0
BloodPressure 0
SkinThickness 0
Insulin 0
BMI 0
DiabetesPedigreeFunction 0
Age 0
Outcome 0
dtype: int64
```

data.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 768 entries, 0 to 767 Data columns (total 9 columns):

		•	
#	Column	Non-Null Count	Dtype
0	Pregnancies	768 non-null	int64
1	Glucose	768 non-null	int64
2	BloodPressure	768 non-null	int64
3	SkinThickness	768 non-null	int64
4	Insulin	768 non-null	int64
5	BMI	768 non-null	float64
6	DiabetesPedigreeFunction	768 non-null	float64
7	Age	768 non-null	int64
8	Outcome	768 non-null	int64
4.4	63 (64/6) (1464/5)		

dtypes: float64(2), int64(7)

memory usage: 54.1 KB

data.describe()

BMI I

```
Pregnancies
                             Glucose BloodPressure SkinThickness
                                                                        Insulin
      count
              768.000000 768.000000
                                          768.000000
                                                          768.000000 768.000000 768.000000
                3.845052 120.894531
                                           69.105469
                                                           20.536458
                                                                      79.799479
                                                                                   31.992578
      mean
       std
                3.369578
                           31.972618
                                           19.355807
                                                           15.952218 115.244002
                                                                                   7.884160
                0.000000
                            0.000000
                                            0.000000
                                                                        0.000000
                                                                                    0.000000
                                                            0.000000
       min
                                           62.000000
       25%
                1.000000
                           99.000000
                                                            0.000000
                                                                        0.000000
                                                                                   27.300000
       50%
                3 000000 117 000000
                                           72 000000
                                                           23 000000
                                                                       30 500000
                                                                                   32.000000
      75%
                6.000000 140.250000
                                           80.000000
                                                           32.000000 127.250000
                                                                                   36.600000
                17.000000 199.000000
                                          122 000000
                                                           99.000000 846.000000
                                                                                   67.100000
       max
data.columns
     dtype='object')
x=data.iloc[:,:-1].values
y=data.iloc[:,-1].values
#training and testing
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)
print(x train)
     [[7.00e+00 1.50e+02 7.80e+01 ... 3.52e+01 6.92e-01 5.40e+01]
      [4.00e+00 9.70e+01 6.00e+01 ... 2.82e+01 4.43e-01 2.20e+01]
      [0.00e+00 1.65e+02 9.00e+01 ... 5.23e+01 4.27e-01 2.30e+01]
      [4.00e+00 9.40e+01 6.50e+01 ... 2.47e+01 1.48e-01 2.10e+01]
      [1.10e+01 8.50e+01 7.40e+01 ... 3.01e+01 3.00e-01 3.50e+01]
[5.00e+00 1.36e+02 8.20e+01 ... 0.00e+00 6.40e-01 6.90e+01]]
#feature scaling using standard scaler
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
x_train= sc.fit_transform(x_train)
x_test=sc.transform(x_test)
print(x_train)
     [[ 0.90832902  0.91569367  0.44912368  ...  0.37852648  0.67740401
      [ \ 0.03644676 \ -0.75182191 \ -0.47230103 \ \dots \ -0.50667229 \ -0.07049698
       -0.96569189]
      [-1.12606292 1.38763205 1.06340683 ... 2.54094063 -0.11855487
       -0.882402831
      [ \ 0.03644676 \ -0.84620959 \ -0.21634972 \ \dots \ -0.94927168 \ -0.95656442
       -1.04898095]
      [\ \ 2.0708387 \ \ -1.12937261 \ \ 0.24436264 \ \dots \ \ -0.26640405 \ \ -0.50001442
        0.11706589]
      [ 0.32707418  0.47521786  0.65388473  ... -4.07275877  0.52121586
        2.94889395]]
from sklearn.tree import DecisionTreeClassifier
model=DecisionTreeClassifier()
model.fit(x_train,y_train)
      ▼ DecisionTreeClassifier
     DecisionTreeClassifier()
y_pred=model.predict(x_test)
np.array((y_pred, y_test ))
     \mathsf{array}([[1,\ 0,\ 0,\ 1,\ 0,\ 0,\ 1,\ 1,\ 0,\ 1,\ 1,\ 0,\ 0,\ 0,\ 1,\ 1,\ 0,\ 0,\ 0,\ 1,\ 0,
             0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1,
```

1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1,

from sklearn.metrics import classification_report,confusion_matrix $print(classification_report(y_test,y_pred))$

	precision	recall	f1-score	support
0	0.88	0.83	0.86	107
1	0.66	0.74	0.70	47
accuracy			0.81	154
macro avg	0.77	0.79	0.78	154
weighted avg	0.81	0.81	0.81	154

print(confusion_matrix(y_test,y_pred))

[[89 18] [12 35]]

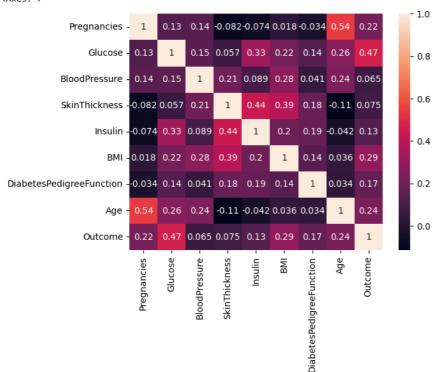
print(data.corr())

	Pregnanci	es	Gluco	se	BloodPressure	SkinThickness	,
Pregnancies	1.0000	00	0.129459		0.141282	-0.081672	
Glucose	0.1294	59	1.0000	00	0.152590	0.057328	
BloodPressure	0.1412	82	0.1525	90	1.000000	0.207371	
SkinThickness	-0.0816	72	0.0573	28	0.207371	1.000000	
Insulin	-0.0735	35	0.3313	57	0.088933	0.436783	
BMI	0.0176	83	0.2210	71	0.281805	0.392573	
DiabetesPedigreeFunction	-0.0335	23	0.1373	37	0.041265	0.183928	
Age	0.5443	41	0.2635	14	0.239528	-0.113970	
Outcome	0.2218	98	0.4665	81	0.065068	0.074752	
	Insulin		BMI	Di	abetesPedigreeF	unction \	
Pregnancies	-0.073535	0.0	017683		-0	.033523	
Glucose	0.331357	0.	221071		0	.137337	
BloodPressure	0.088933	0.	281805		0	.041265	
SkinThickness	0.436783	0.	392573		0	.183928	
Insulin	1.000000	0.	197859		0	.185071	
BMI	0.197859	1.0	000006		0	.140647	
DiabetesPedigreeFunction	0.185071	0.	140647		1	.000000	
Age	-0.042163	0.0	ð36242		0	.033561	
Outcome	0.130548	0.	292695		0	.173844	
	Age	0	utcome				
Pregnancies	0.544341	0.	221898				
Glucose	0.263514	0.4	466581				
BloodPressure	0.239528	0.0	965968				
SkinThickness	-0.113970	0.0	074752				
Insulin	-0.042163	0.3	130548				
BMI	0.036242	0.	292695				
${\tt DiabetesPedigreeFunction}$	0.033561	0.	173844				
Age	1.000000	0.	238356				
Outcome	0.238356	1.0	900000				

import seaborn as sns

sns.heatmap(data.corr(),annot=True)

<Axes: >



```
from sklearn.ensemble import BaggingClassifier
from sklearn.metrics import accuracy score
base_model = DecisionTreeClassifier(random_state=42)
bagging_model_dt = BaggingClassifier(base_model, n_estimators=10, random_state=42)
\ensuremath{\text{\#}} Train and evaluate the bagging classifier with decision trees
bagging_model_dt.fit(x_train, y_train)
y_pred_dt = bagging_model_dt.predict(x_test)
accuracy_dt = accuracy_score(y_test, y_pred_dt)
print("Bagging Classifier with Decision Trees Accuracy:", accuracy_dt)
     Bagging Classifier with Decision Trees Accuracy: 0.7857142857142857
2nd data accuracy
x=data.iloc[:,:-3].values
y=data.iloc[:,-1].values
#training and testing
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)
print(x_train)
     [[ 7. 150.
                    78.
                          29. 126.
                                       35.2]
         4.
              97.
                                       28.2]
                    60.
                          23.
                                  0.
        0.
                                680.
             165.
                    90.
                          33.
                                       52.31
      [
        4.
                    65.
                                  0.
                                       24.71
              94.
                           22.
        11.
              85.
                    74.
                           0.
                                  0.
                                       30.1]
        5.
            136.
                    82.
                           0.
                                  0.
                                        0.]]
#feature scaling using standard scaler
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
x_train= sc.fit_transform(x_train)
x_test=sc.transform(x_test)
from sklearn.tree import DecisionTreeClassifier
```

model=DecisionTreeClassifier()
model.fit(x_train,y_train)

```
v DecisionTreeClassifier
DecisionTreeClassifier()
```

y_pred=model.predict(x_test)

from sklearn.metrics import classification_report,confusion_matrix
print(classification_report(y_test,y_pred))

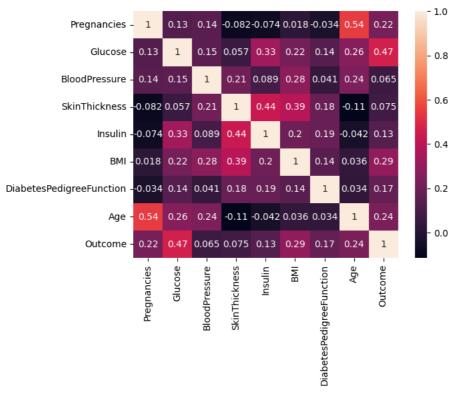
	precision	recall	f1-score	support
0	0.83	0.82	0.83	107
1	0.60	0.62	0.61	47
accuracy macro avg weighted avg	0.72 0.76	0.72 0.76	0.76 0.72 0.76	154 154 154

print(confusion_matrix(y_test,y_pred))

[[88 19] [18 29]]

import seaborn as sns
sns.heatmap(data.corr(),annot=True)

→ <Axes: >



```
from sklearn.ensemble import BaggingClassifier
from sklearn.metrics import accuracy_score
base_model = DecisionTreeClassifier(random_state=42)
bagging_model_dt = BaggingClassifier(base_model, n_estimators=10, random_state=42)
#classifier with decision trees
bagging_model_dt.fit(x_train, y_train)
y_pred_dt = bagging_model_dt.predict(x_test)
accuracy_dt = accuracy_score(y_test, y_pred_dt)
print("Bagging Classifier with DT Accuracy:", accuracy_dt)
```

Bagging Classifier with DT Accuracy: 0.7662337662337663