EXP NO:1 STUDY ON PYTHON PACKAGES

25/01/25

AIM:

To study about python packages required to work with Data Analytics (Numpy, Pandas, Statsmodels, Scipy)

NUMPY:

NumPy is the fundamental package for scientific computing in Python. It is a Python library that provides a multidimensional array object, various derived objects (such as masked arrays and matrices), and an assortment of routines for fast operations on arrays, including mathematical, logical, shape manipulation, sorting, selecting, I/O, discrete Fourier transforms, basic linear algebra, basic statistical operations, random simulation and much more.

```
import numpy as np
arr = np.array([5, 10, 15])
print('First array is:')
print(arr)
print('\nApplying power fn:')
print(np.power(arr, 2))
print('\nSecond array is:')
arr1 = np.array([1, 2, 3])
print(arr1)
print('\nApplying power function again:')
print(np.power(arr, arr1))
```

OUPUT:

```
First array is:
[ 5 10 15]

Applying power fn:
[ 25 100 225]

Second array is:
[1 2 3]

Applying power function again:
[ 5 100 3375]
```

PANDAS:

Pandas is a Python package that provides fast, flexible, and expressive data structures designed to make working with "relational" or "labeled" data both easy and intuitive. It aims to be the fundamental high-level building block for doing practical, real world data analysis in Python. Additionally, it has the broader goal of becoming the most powerful and flexible open source data analysis / manipulation tool available in any language. It is already well on its way towards this goal.

```
import pandas as pd

Ist=['sai', 'saber', 'ashwin', 'madhav']

df = pd.DataFrame(Ist)

print(df)

import pandas as pd

technologies = {

'Courses':["WT","CN","CE","PR",None],

'Fee':[20000,25000,22000,None,30000],
```

```
'Duration':['30days','40days','35days','None','50days'],
'Discount':[1000,2300,1200,2000,None]}
index_labels=['r1','r2','r3','r4','r5']
df = pd.DataFrame(technologies,index=index_labels)
print(df)
```

OUTPUT:

```
0
0 sai
1 saber
2 ashwin
3 madhav
```

C	ourses	Fee	Duration	Discount
r1	WT	20000.0	30days	1000.0
r2	CN	25000.0	40days	2300.0
r3	CE	22000.0	35days	1200.0
r4	PR	NaN	None	2000.0
r5	None	30000.0	50days	NaN

STATSMODELS:

Statsmodels is a Python module that provides classes and functions for the estimation of many different statistical models, as well as for conducting statistical tests, and statistical data exploration. An extensive list of result statistics are available for each estimator. The results are tested against existing statistical packages to ensure that they are correct. The package is released under the open source Modified BSD (3-clause) license.

SCIPY:

SciPy is a python library that is useful in solving many mathematical equations and algorithms. It is designed on the top of Numpy library that gives more extension of finding scientific mathematical formulae like Matrix Rank, Inverse, polynomial equations, LU Decomposition, etc. Using its high level functions will significantly reduce the complexity of the code and helps in better analyzing the data. SciPy is an interactive Python session used as a data-processing library that is made to compete with its rivalries such as MATLAB, Octave, R-Lab, etc. It has many user-friendly, efficient and easy-to-use functions that helps to solve problems like numerical integration, interpolation, optimization, linear algebra and statistics.

```
> from scipy import linalg
import numpy as np

two_d_array = np.array([ [4,5], [3,2] ])
linalg.det( two_d_array )

> from scipy import poly1d
poly=poly1d([1,3,9]) #creating the polynomial
print("The polynomial is:\n",poly)
print("The value of the polynomial for the value of x=3 is:\n",poly(3))
print("The product of the polynomial with itself is:\n",poly*poly)
print("The integration of the polynomial is:\n",poly.integ(k=5))
print("The differentiation of the polynomial is:\n",poly.deriv())

OUTPUT:

Out[12]: -7.0
```

```
The polynomial is:

2

1 x + 3 x + 9

The value of the polynomial for the value of x=3 is:

27

The product of the polynomial with itself is:

4 3 2

1 x + 6 x + 27 x + 54 x + 81

The integration of the polynomial is:

3 2

0.3333 x + 1.5 x + 9 x + 5

The differentiation of the polynomial is:

2 x + 3
```

EXP NO:2 **DESCRIPTIVE ANALYSIS**

08/02/23

AIM:

To explore the various commands for performing descriptive data analysis on various dataset.

CODE:

```
import pandas as pd

df = pd.read_csv("Iris.csv")

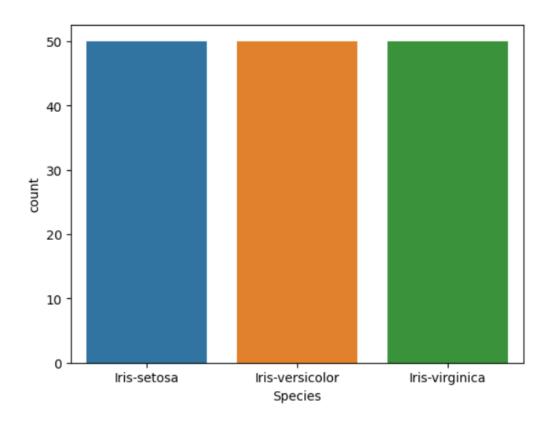
df.head()
```

Out[14]:		ld	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
	0	1	5.1	3.5	1.4	0.2	Iris-setosa
	1	2	4.9	3.0	1.4	0.2	Iris-setosa
	2	3	4.7	3.2	1.3	0.2	Iris-setosa
	3	4	4.6	3.1	1.5	0.2	Iris-setosa
	4	5	5.0	3.6	1 4	0.2	Iris-setosa

df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
# Column
                    Non-Null Count Dtype
_ _ _
0
     Id
                     150 non-null
                                      int64
     SepalLengthCm 150 non-null
                                      float64
1
     SepalWidthCm 150 non-null
PetalLengthCm 150 non-null
                                      float64
                                      float64
     PetalWidthCm 150 non-null
                                      float64
                     150 non-null
     Species
                                      object
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

import seaborn as sns
import matplotlib.pyplot as plt
sns.countplot(x='Species', data=df,)
plt.show()



df.isnull().sum()/len(df)*100

Out[5]:	Id	0.0
	SepalLengthCm	0.0
	SepalWidthCm	0.0
	PetalLengthCm	0.0
	PetalWidthCm	0.0
	Species	0.0
	dtype: float64	

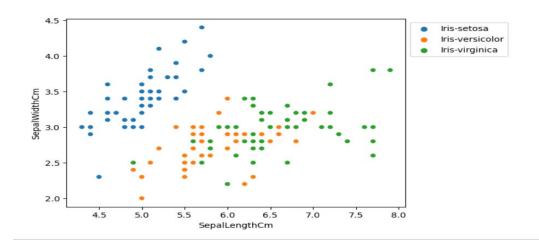
K-squared test

```
print(["PetalWidthCm"])
a, b = stats.normaltest(df[["PetalWidthCm"]])
print(a, b)
alpha = 0.05
if b < alpha:
print("Null hypotheses can be rejected")
else:
print("Null hypotheses cannot be rejected")

['PetalWidthCm']
[136.77701788] [1.99181015e-30]
Null hypotheses can be rejected</pre>
```

> import seaborn as sns

```
sns.scatterplot(x='SepalLengthCm',y='SepalWidthCm',hue='Species',
data=df, )
plt.legend(bbox_to_anchor=(1, 1), loc=2)
plt.show()
```



import pandas as pd

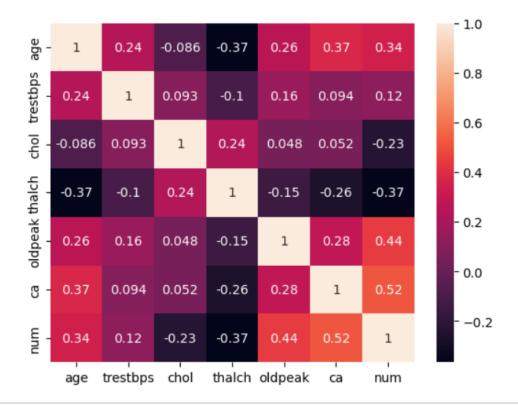
df = pd.read_csv("heartdisease.csv")

df.head()

Out[1]:		id	age	sex	dataset	ср	trestbps	chol	fbs	restecg	thalch	exang	oldpeak	slope	ca	thal	num
	0	1	63	Male	Cleveland	typical angina	145.0	233.0	True	lv hypertrophy	150.0	False	2.3	downsloping	0.0	fixed defect	0
	1	2	67	Male	Cleveland	asymptomatic	160.0	286.0	False	lv hypertrophy	108.0	True	1.5	flat	3.0	normal	2
	2	3	67	Male	Cleveland	asymptomatic	120.0	229.0	False	lv hypertrophy	129.0	True	2.6	flat	2.0	reversable defect	1
	3	4	37	Male	Cleveland	non-anginal	130.0	250.0	False	normal	187.0	False	3.5	downsloping	0.0	normal	0
	4	5	41	Female	Cleveland	atypical angina	130.0	204.0	False	lv hypertrophy	172.0	False	1.4	upsloping	0.0	normal	0

sns.heatmap(df.corr(method='pearson').drop(['id'], axis=1).drop(['id'],
axis=0), annot = True);

plt.show()



```
sum_data = df["oldpeak"].sum()
mean_data = df["oldpeak"].mean()
median_data = df["oldpeak"].median()
mode_data = df["oldpeak"].mode()
print("Sum:",sum_data, "\nMean:", mean_data, "\nMedian:",median_data,
"\nMode:" ,mode_data)
Sum: 754.0
Mean: 0.87878787878787
Median: 0.5
Mode: 0 0.0
Name: oldpeak, dtype: float64
```

df.skew()

```
Out[3]: id
                    0.000000
                   -0.195994
                    0.213334
        trestbps
        chol
                   -0.613836
        fbs
                   1.795987
        thalch
                   -0.211119
        exang
                    0.453582
        oldpeak
                    1.041427
                    1.165978
        ca
                    0.968880
        dtype: float64
```

df.kurt()

```
Out[4]: id -1.200000
age -0.382930
        trestbps 2.958664
        chol
                  0.062273
        fbs
                  1.228523
        thalch
                  -0.479725
        exang
                  -1.798427
        oldpeak
                  1.127069
        ca
                   0.199498
        num
                  -0.104325
        dtype: float64
```

RESULT:

Thus, the various commands for performing descriptive data analysis on the Iris Dataset have been executed and verified.

EXP NO:3 UNI, BI AND MULTI-VARIATE ANALYSIS

08/02/23

AIM:

To perform uni, bi and multi-variate analysis on the Diabetes dataset.

CODE:

import pandas as pd

df = pd.read_csv("diabetes1.csv")

df.head()

Out[1]:		Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	вмі	DiabetesPedigreeFunction	Age	Outcome
	0	6	148	72	35	0	33.6	0.627	50	1
	1	1	85	66	29	0	26.6	0.351	31	0
	2	8	183	64	0	0	23.3	0.672	32	1
	3	1	89	66	23	94	28.1	0.167	21	0
	4	0	137	40	35	168	43.1	2.288	33	1

➤ df.shape

df.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

dtypes: float64(2), int64(7)
memory usage: 54.1 KB

df.describe()

Out[4]:		Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	ВМІ	DiabetesPedigreeFunction	Age	Outcome
	count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000
	mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.240885	0.348958
	std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232	0.476951
	min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	0.000000
	25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000	0.000000
	50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000	0.000000
	75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	1.000000
	max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	1.000000

df.isnull().sum()

Out[5]:	Pregnancies	0
	Glucose	0
	BloodPressure	0
	SkinThickness	0
	Insulin	0
	BMI	0
	DiabetesPedigreeFunction	0
	Age	0
	Outcome	0
	dtype: int64	

df.value_counts("Outcome")

Out[7]: Outcome 0 500 1 268 dtype: int64

```
> sum_data = df["SkinThickness"].sum()
mean_data = df["SkinThickness"].mean()
median_data = df["SkinThickness"].median()
mode_data = df["SkinThickness"].mode()
print("Sum:",sum_data, "\nMean:", mean_data, "\nMedian:",median_data,
"\nMode:",mode_data)
```

Sum: 15772

Mean: 20.536458333333333

Median: 23.0 Mode: 0 0

Name: SkinThickness, dtype: int64

df.skew()

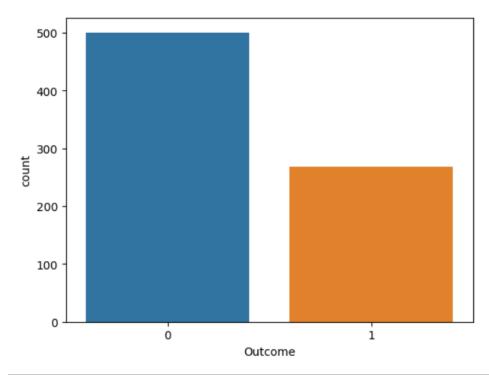
Pregnancies	0.901674
Glucose	0.173754
BloodPressure	-1.843608
SkinThickness	0.109372
Insulin	2.272251
BMI	-0.428982
DiabetesPedigreeFunction	1.919911
Age	1.129597
Outcome	0.635017
dtype: float64	
	Glucose BloodPressure SkinThickness Insulin BMI DiabetesPedigreeFunction Age Outcome

df.kurt()

Out[28]:	Pregnancies	0.159220
	Glucose	0.640780
	BloodPressure	5.180157
	SkinThickness	-0.520072
	Insulin	7.214260
	BMI	3.290443
	DiabetesPedigreeFunction	5.594954
	Age	0.643159
	Outcome	-1.600930
	dtype: float64	

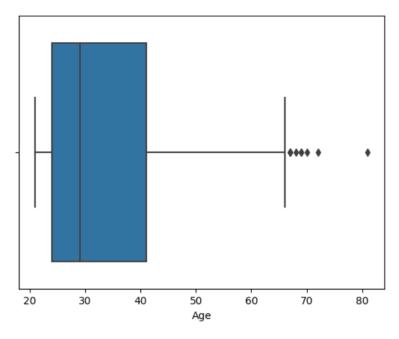
> import seaborn as sns

import matplotlib.pyplot as plt
sns.countplot(x='Outcome', data=df,)
plt.show()

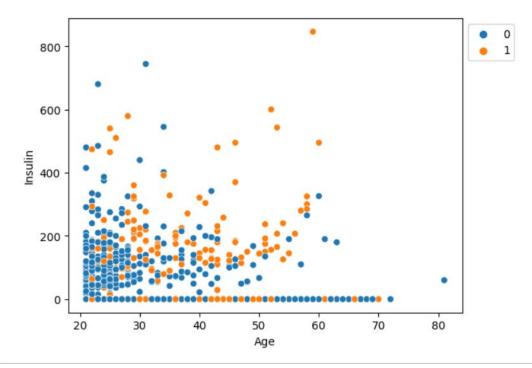


sns.boxplot(x='Age', data=df)

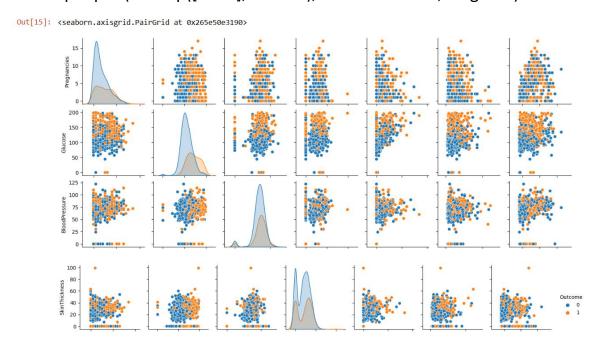
Out[12]: <AxesSubplot: xlabel='Age'>

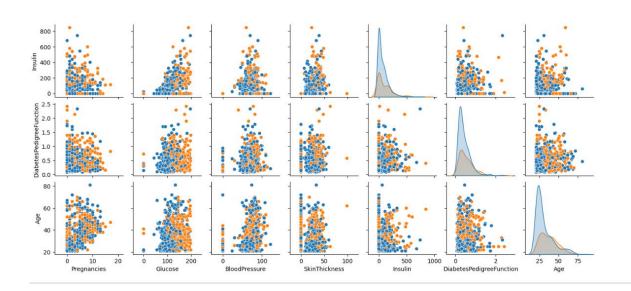


> sns.scatterplot(x='Age', y='Insulin', hue='Outcome', data=df,)
plt.legend(bbox_to_anchor=(1, 1), loc=2)
plt.show()

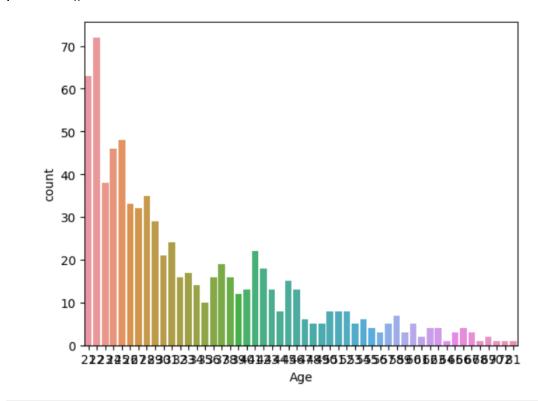


> sns.pairplot(df.drop(['BMI'], axis = 1), hue='Outcome', height=2)



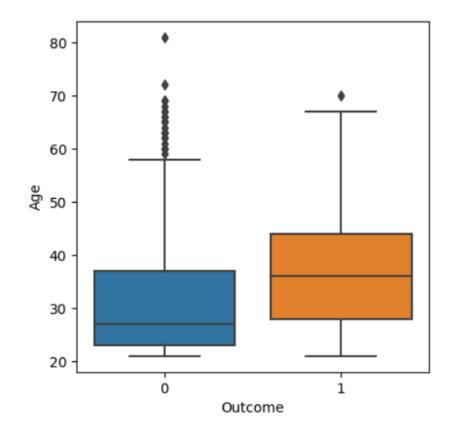


sns.countplot(x="Age", data=df,)
plt.show()

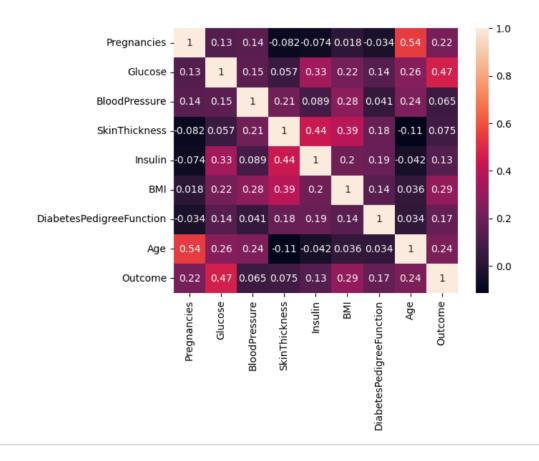


def graph(y):
sns.boxplot(x="Outcome", y=y, data=df)
plt.figure(figsize=(10,10))

plt.subplot(221) graph("Age")



sns.heatmap(df.corr(method='pearson'), annot = True);
plt.show()



RESULT:

Thus, uni, bi and multi-variate analysis on the Diabetes dataset has been performed and verified.

EXP NO:3

REGRESSIONS

22/02/23

AIM:

To perform various types of Regression on the iris and diabetes dataset.

CODE:

1. LINEAR REGRESSION:

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
import seaborn as sns

df = pd.read_csv('iris1.csv')
df.head()

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	sepal.length	sepal.width	petal.length	petal.width	variety
0	5.1	3.5	1.4	0.2	Setosa
1	4.9	3.0	1.4	0.2	Setosa
2	4.7	3.2	1.3	0.2	Setosa
3	4.6	3.1	1.5	0.2	Setosa
4	5.0	3.6	1.4	0.2	Setosa

df['variety'].value counts()

```
Out[25]: Setosa 50
Versicolor 50
Virginica 50
Name: variety, dtype: int64
```

def getPredictions(flowerValues, xLabel, yLabel):
X = np.array(flowerValues[xLabel]).reshape(-1,1)
y = np.array(flowerValues[yLabel]).reshape(-1,1)
reg = LinearRegression().fit(X, y)
y_pred = reg.predict(X)
return y_pred

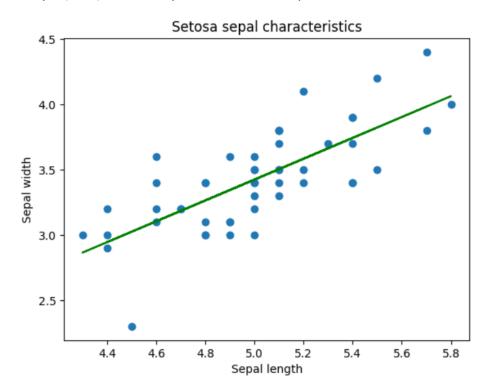
>> setosa = df[df['variety'] == 'Setosa']
setosa = setosa.loc[:, setosa.columns != 'variety']
setosa.columns = ['sepalLength', 'sepalWidth', 'petalLength', 'petalWidth']
setosa.head()

Out[27]:		sepalLength	sepalWidth	petalLength	petalWidth
	0	5.1	3.5	1.4	0.2
	1	4.9	3.0	1.4	0.2
	2	4.7	3.2	1.3	0.2
	3	4.6	3.1	1.5	0.2
	4	5.0	3.6	1.4	0.2

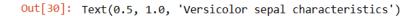
y_pred = getPredictions(setosa, 'sepalLength', 'sepalWidth')
plt.scatter(setosa['sepalLength'], setosa['sepalWidth'])
plt.plot(setosa['sepalLength'], y_pred, color='g')
plt.xlabel('Sepal length')

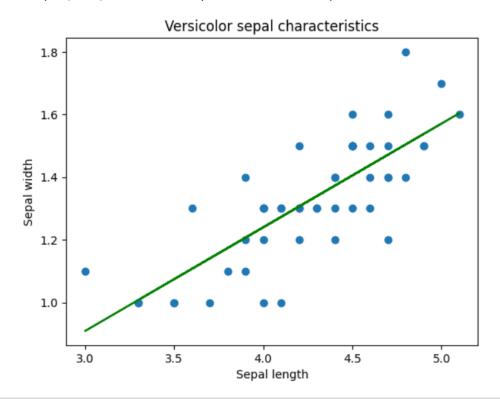
plt.ylabel('Sepal width')
plt.title('Setosa sepal characteristics')

Out[28]: Text(0.5, 1.0, 'Setosa sepal characteristics')



y_pred = getPredictions(versicolor, 'petalLength', 'petalWidth')
plt.scatter(versicolor['petalLength'], versicolor['petalWidth'])
plt.plot(versicolor['petalLength'], y_pred, color='g')
plt.xlabel('Sepal length')
plt.ylabel('Sepal width')
plt.title('Versicolor sepal characteristics')





2. LOGISTIC REGRESSION:

> import pandas as pd

import numpy as np

import seaborn as sns

import matplotlib.pyplot as plt

from sklearn.linear_model import LogisticRegression

df = pd.read_csv("diabetes1.csv", names=col_names, header=0)
df.head()

Out[35]:		pregnant	glucose	bp	skin	insulin	bmi	pedigree	age	label
	0	6	148	72	35	0	33.6	0.627	50	1
	1	1	85	66	29	0	26.6	0.351	31	0
	2	8	183	64	0	0	23.3	0.672	32	1
	3	1	89	66	23	94	28.1	0.167	21	0
	4	0	137	40	35	168	43.1	2.288	33	1

#split dataset in features and target variable

feature_cols = ['pregnant', 'insulin', 'bmi', 'age','glucose','bp','pedigree']

X = df[feature_cols] # Features

y = df.label # Target variable

split X and y into training and testing sets

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,
random_state=16)

import the class

➤ from sklearn.linear_model import LogisticRegression

instantiate the model (using the default parameters)

logreg = LogisticRegression(random_state=16)

fit the model with data

➤ logreg.fit(X_train, y_train)

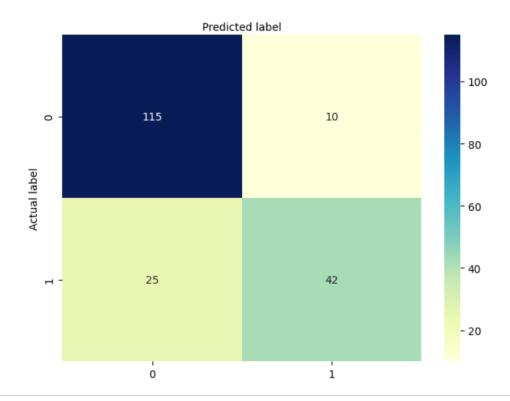
y_pred = logreg.predict(X_test)

```
logreg.score(X test, y test)
 Out[39]: 0.8177083333333334
# import the metrics class
> from sklearn import metrics
cnf_matrix = metrics.confusion_matrix(y_test, y_pred)
cnf_matrix
Out[40]: array([[115, 10],
                 [ 25, 42]], dtype=int64)
# import required modules
> import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
class_names=[0,1] # name of classes
fig, ax = plt.subplots()
tick marks = np.arange(len(class names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
# create heatmap
sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YIGnBu"
   ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
```

plt.ylabel('Actual label') plt.xlabel('Predicted label')

Out[41]: Text(0.5, 427.95555555555, 'Predicted label')

Confusion matrix



from sklearn.metrics import classification_report target_names = ['without diabetes', 'with diabetes'] print(classification_report(y_test, y_pred, target_names=target_names))

	precision	recall	f1-score	support
without diabetes	0.82	0.92	0.87	125
with diabetes	0.81	0.63	0.71	67
accuracy			0.82	192
macro avg	0.81	0.77	0.79	192
weighted avg	0.82	0.82	0.81	192

3. MULTIPLE REGRESSION:

> import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LinearRegression

import seaborn as sns

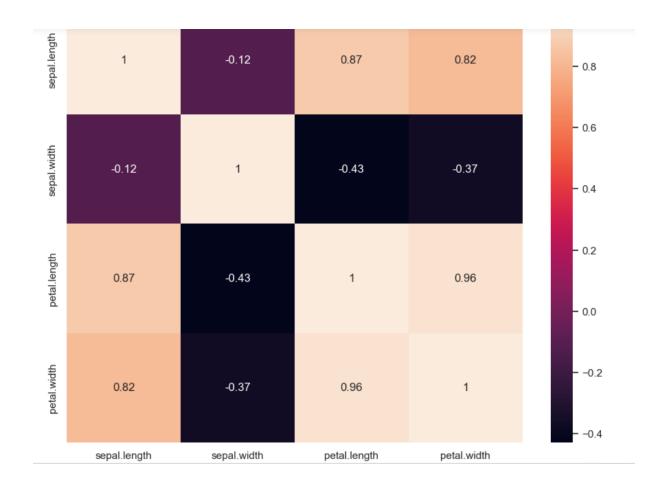
df = pd.read_csv('iris1.csv')
df.head()

Out[11]:

	sepal.length	sepal.width	petal.length	petal.width	variety
0	5.1	3.5	1.4	0.2	Setosa
1	4.9	3.0	1.4	0.2	Setosa
2	4.7	3.2	1.3	0.2	Setosa
3	4.6	3.1	1.5	0.2	Setosa
4	5.0	3.6	1.4	0.2	Setosa

sns.set(rc={'figure.figsize':(10.7,8.27)})

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



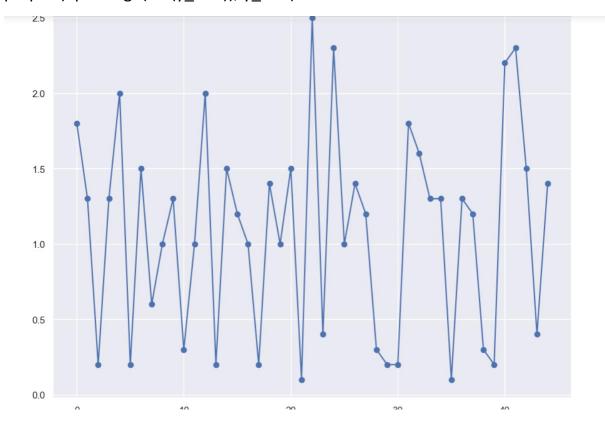
independant_vars = ['petal.width', 'sepal.width', 'petal.length']
feature =np.array(df[independant_vars]).reshape(-1,len(independant_vars))
res = np.array(df['petal.width']).reshape(-1,1)
X_train,X_test,y_train,y_test=train_test_split(feature,res,test_size=0.3)

#model and training

model=LinearRegression()
fittedModel=model.fit(X_train,y_train)
predictions=fittedModel.predict(X_test)
fittedModel.score(X_test,y_test)

Out[14]: 1.0

plt.scatter(np.arange(len(y_test)), predictions)
plt.plot(np.arange(len(y_test)), y_test)



RESULT:

Thus, various types of regression using iris and diabetes dataset has been implemented and verified successfully.

EXP NO:5 BAYESIAN CLASSIFIER AND SVM

01/01/23

AIM:

To perform Bayesian classifier and Support Vector Machine(SVM) on both iris and diabetes dataset.

CODE:

1. BAYESIAN CLASSIFIER:

import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix, accuracy_score
import seaborn as sns

df = pd.read_csv("iris1.csv")
df.head()

	sepal.length	sepal.width	petal.length	petal.width	variety
0	5.1	3.5	1.4	0.2	Setosa
1	4.9	3.0	1.4	0.2	Setosa
2	4.7	3.2	1.3	0.2	Setosa
3	4.6	3.1	1.5	0.2	Setosa
4	5.0	3.6	1.4	0.2	Setosa
	1 2 3	 0 5.1 1 4.9 2 4.7 3 4.6 	0 5.1 3.5 1 4.9 3.0 2 4.7 3.2 3 4.6 3.1	0 5.1 3.5 1.4 1 4.9 3.0 1.4 2 4.7 3.2 1.3 3 4.6 3.1 1.5	1 4.9 3.0 1.4 0.2 2 4.7 3.2 1.3 0.2 3 4.6 3.1 1.5 0.2

```
X = df.iloc[:,:4].values
y = df['variety'].values
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)
sc = StandardScaler()
X train = sc.fit transform(X train)
```

X_test = sc.transform(X_test)

classifier = GaussianNB()
classifier.fit(X_train, y_train)

```
Out[13]: GaussianNB()
```

y_pred = classifier.predict(X_test)

y_pred

```
Out[14]: array(['Versicolor', 'Setosa', 'Versicolor', 'Versicolor', 'Virginica', 'Setosa', 'Versicolor', 'Versicolor', 'Virginica', 'Setosa', 'Versicolor', 'Virginica', 'Setosa', 'Virginica', 'Virginica', 'Setosa', 'Virginica', 'Setosa', 'Setosa', 'Setosa', 'Setosa', 'Setosa', 'Virginica', 'Setosa', 'Virginica', 'Setosa', 'Virginica', 'Setosa', 'Virginica', 'Versicolor', 'Virginica', 'Setosa'], dtype='<U10')
```

print ("Accuracy : ", accuracy_score(y_test, y_pred))

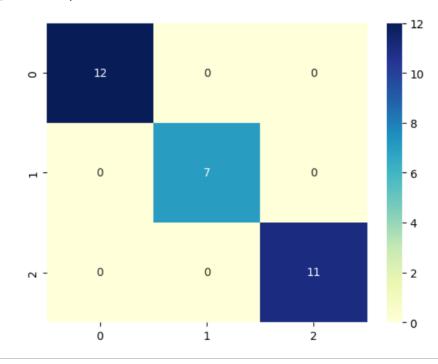
Accuracy : 1.0

cm = confusion_matrix(y_test, y_pred)

cm

> sns.heatmap(cm, annot=True, cmap="YlGnBu")

Out[17]: <AxesSubplot:>



df = pd.read_csv("diabetes1.csv")

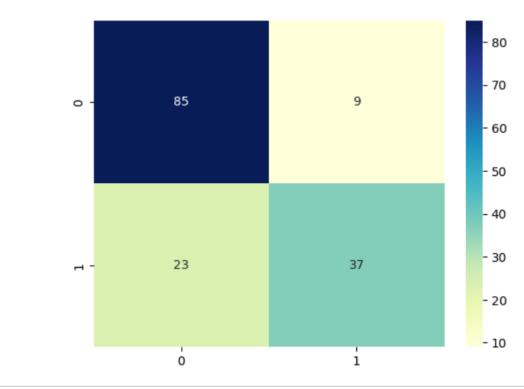
df.head()

out[20]:		Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	ВМІ	DiabetesPedigreeFunction	Age	Outcome
	0	6	148	72	35	0	33.6	0.627	50	1
	1	1	85	66	29	0	26.6	0.351	31	0
	2	8	183	64	0	0	23.3	0.672	32	1
	3	1	89	66	23	94	28.1	0.167	21	0
	4	0	137	40	35	168	43.1	2.288	33	1

```
X = df.iloc[:,:8].values
y = df['Outcome'].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)
sc = StandardScaler()
X train = sc.fit transform(X train)
X_test = sc.transform(X_test)
classifier = GaussianNB()
classifier.fit(X_train, y_train)
y pred = classifier.predict(X test)
y pred
  Out[24]:
            array([0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1,
                   1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
                   1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0,
                   0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0,
                   1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0,
                   0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1],
                  dtype=int64)
print ("Accuracy : ", accuracy_score(y_test, y_pred))
      Accuracy: 0.7922077922077922
cm = confusion matrix(y test, y pred)
cm
 Out[26]: array([[85, 9],
                     [23, 37]], dtype=int64)
```

> sns.heatmap(cm, annot=True, cmap="YlGnBu")

Out[27]: <AxesSubplot:>



2. SUPPORT VECTOR MACHINE(SVM):

df = pd.read_csv("iris1.csv")
df.head()

Out[29]:

	sepal.length	sepal.width	petal.length	petal.width	variety
0	5.1	3.5	1.4	0.2	Setosa
1	4.9	3.0	1.4	0.2	Setosa
2	4.7	3.2	1.3	0.2	Setosa
3	4.6	3.1	1.5	0.2	Setosa
4	5.0	3.6	1.4	0.2	Setosa

X = df.iloc[:,:4].values

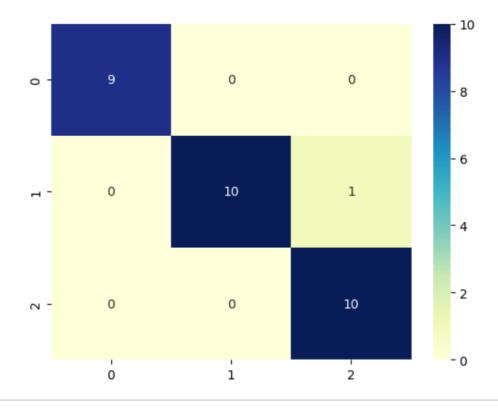
y = df['variety'].values

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X test = sc.transform(X test)
accuracy lin = linear.score(X test, y test)
accuracy_poly = poly.score(X_test, y_test)
accuracy rbf = rbf.score(X test, y test)
accuracy sig = sig.score(X test, y test)
print("Accuracy Linear Kernel:", accuracy_lin)
print("Accuracy Polynomial Kernel:", accuracy poly)
print("Accuracy Radial Basis Kernel:", accuracy rbf)
print("Accuracy Sigmoid Kernel:", accuracy sig)
 Accuracy Linear Kernel: 0.966666666666667
 Accuracy Polynomial Kernel: 0.866666666666667
 Accuracy Radial Basis Kernel: 1.0
 Accuracy Sigmoid Kernel: 0.8
cf matrix linear = confusion matrix(y test, linear.predict(X test))
```

cf matrix poly = confusion matrix(y test, linear.predict(X test))

cf_matrix_rbf = confusion_matrix(y_test, linear.predict(X_test))

Out[35]: <AxesSubplot:>



df = pd.read_csv("diabetes1.csv")
df.head()

Out[38]:		Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	вмі	DiabetesPedigreeFunction	Age	Outcome
	0	6	148	72	35	0	33.6	0.627	50	1
	1	1	85	66	29	0	26.6	0.351	31	0
	2	8	183	64	0	0	23.3	0.672	32	1
	3	1	89	66	23	94	28.1	0.167	21	0
	4	0	137	40	35	168	43.1	2.288	33	1

X = df.iloc[:,:8].values

y = df['Outcome'].values

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)

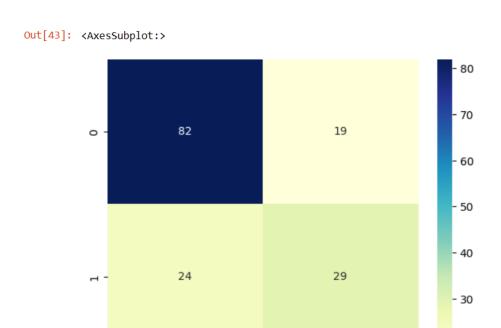
sc = StandardScaler()

X_train = sc.fit_transform(X_train)

X_test = sc.transform(X_test)

```
linear=svm.SVC(kernel='linear',C=1,decision function shape='ovo').fit(X
   _train, y_train)
rbf=svm.SVC(kernel='rbf',gamma=1,C=1,decision function shape='ovo').fit(
X_train, y_train)
poly=svm.SVC(kernel='poly',degree=3,C=1,decision function shape='ovo').f
it(X train, y train)
sig=svm.SVC(kernel='sigmoid',C=1,decision function shape='ovo').fit(X trai
n, y train)
accuracy_lin = linear.score(X_test, y_test)
accuracy poly = poly.score(X test, y test)
accuracy rbf = rbf.score(X test, y test)
accuracy sig = sig.score(X test, y test)
print("Accuracy Linear Kernel:", accuracy_lin)
print("Accuracy Polynomial Kernel:", accuracy poly)
print("Accuracy Radial Basis Kernel:", accuracy rbf)
print("Accuracy Sigmoid Kernel:", accuracy_sig)
 Accuracy Linear Kernel: 0.7207792207792207
 Accuracy Polynomial Kernel: 0.6948051948051948
 Accuracy Radial Basis Kernel: 0.7402597402597403
 Accuracy Sigmoid Kernel: 0.7142857142857143
```

sns.heatmap(confusion_matrix(y_test,linear.predict(X_test)),annot=True , cmap="YIGnBu")



RESULT:

Thus, Bayesian Classifier and Support Vector Machine has been performed on both iris and diabetes dataset and has been verified.

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EXP NO:6

VISUALIZATION

08/03/23

AIM:

To perform Visualization on both iris and diabetes dataset using the libraries like matplotlib and seaborn.

CODE:

> import matplotlib.pyplot as plt

import pandas as pd

import numpy as np

import seaborn as sns

df = pd.read_csv("iris1.csv")

df.head()

Out[2]:

	sepal.length	sepal.width	petal.length	petal.width	variety
0	5.1	3.5	1.4	0.2	Setosa
1	4.9	3.0	1.4	0.2	Setosa
2	4.7	3.2	1.3	0.2	Setosa
3	4.6	3.1	1.5	0.2	Setosa
4	5.0	3.6	1.4	0.2	Setosa

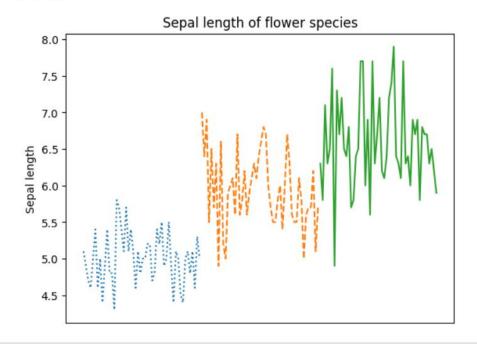
> setosa = df[df['variety'] == 'Setosa']
versicolor = df[df['variety'] == 'Versicolor']

```
virginica = df[df['variety'] == 'Virginica']
df['variety'].value_counts()
```

```
Out[3]: Setosa 50
Versicolor 50
Virginica 50
Name: variety, dtype: int64
```

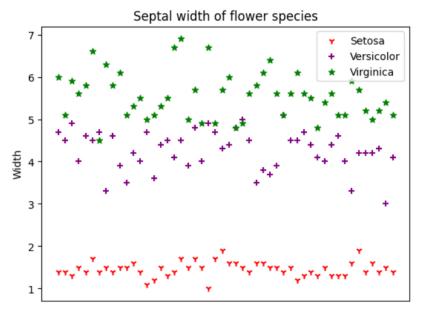
```
plt.plot(setosa['sepal.length'], ls=':')
plt.plot(versicolor['sepal.length'], ls='--')
plt.plot(virginica['sepal.length'])
plt.ylabel("Sepal length")
plt.title("Sepal length of flower species")
plt.xticks([])
```

Out[4]: ([], [])



plt.scatter(np.arange(len(setosa.index)),(setosa['petal.length']),marker='
1', c='red', label='Setosa')

```
plt.scatter(np.arange(len(versicolor.index)),(versicolor['petal.length']),marker='
+', c='purple', label='Versicolor')
plt.scatter(np.arange(len(virginica.index)),(virginica['petal.length']), marker='*',
c='g', label='Virginica')
plt.ylabel("Width")
plt.title("Septal width of flower species")
plt.legend()
plt.xticks([])
out[5]: ([], [])
```



plt.bar([1],setosa['petal.length'].mean(), width=0.4, label='setosa',
color='olive')

plt.bar([1.7],versicolor['petal.length'].mean(),width=0.4,label='versicolor',color ='slategray')

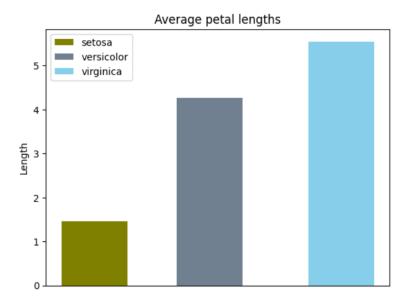
plt.bar([2.5],virginica['petal.length'].mean(),width=0.4,label='virginica',color= 'skyblue')

plt.legend()

plt.ylabel("Length")

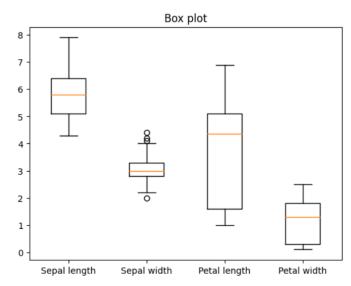
plt.title("Average petal lengths")
plt.xticks([])

Out[6]: ([], [])

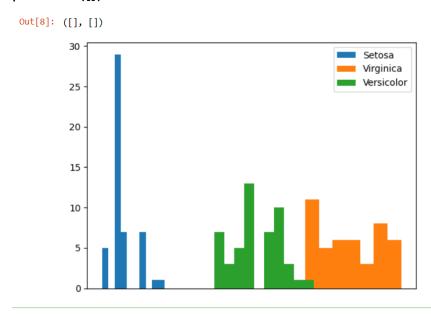


without_species = df.drop('variety', axis=1)
transposed_without_species = without_species.transpose()
plt.boxplot(without_species)
plt.xticks([1,2,3,4], ['Sepal length', 'Sepal width', 'Petal length', 'Petal width'])
plt.title("Box plot")

Out[7]: Text(0.5, 1.0, 'Box plot')



plt.hist(setosa['petal.width'], label='Setosa')
plt.hist(virginica['petal.width'], label='Virginica')
plt.hist(versicolor['petal.width'], label='Versicolor')
plt.legend()
plt.xticks([])



> sns.heatmap(df.corr(method='pearson'),annot = True);
plt.show()



df = pd.read_csv("diabetes1.csv")
df.head()

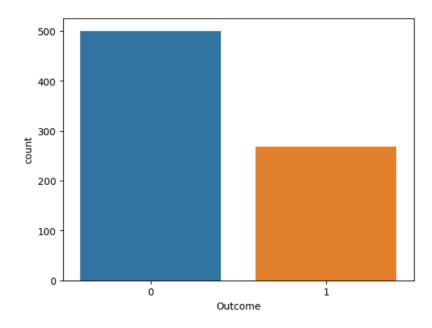
Out[10]:		Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	вмі	DiabetesPedigreeFunction	Age	Outcome
	0	6	148	72	35	0	33.6	0.627	50	1
	1	1	85	66	29	0	26.6	0.351	31	0
	2	8	183	64	0	0	23.3	0.672	32	1
	3	1	89	66	23	94	28.1	0.167	21	0
	4	0	137	40	35	168	43.1	2.288	33	1

> one = df[df['Outcome'] == 1]
zero = df[df['Outcome'] == 0]
df['Outcome'].value_counts()

Out[14]: 0 500 1 268

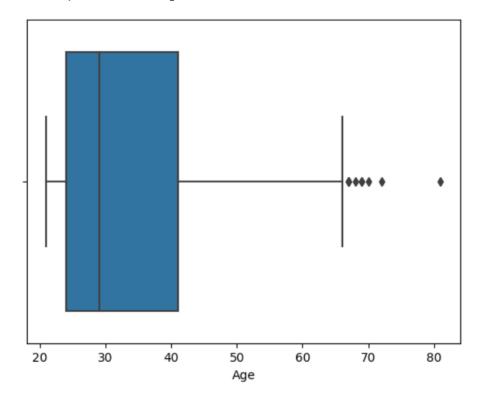
Name: Outcome, dtype: int64

import seaborn as sns
import matplotlib.pyplot as plt
sns.countplot(x='Outcome', data=df,)
plt.show()

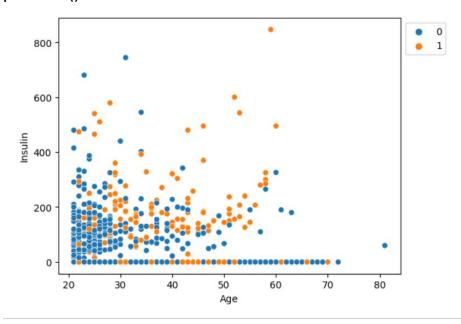


sns.boxplot(x='Age', data=df)

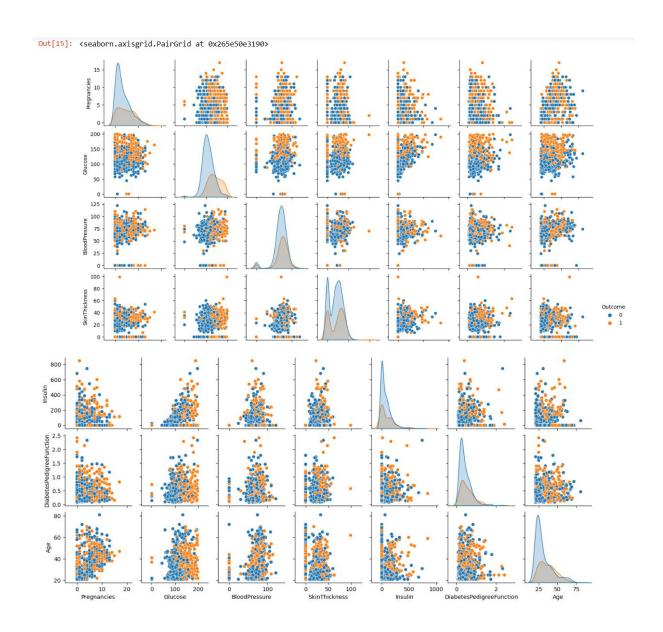
Out[12]: <AxesSubplot: xlabel='Age'>



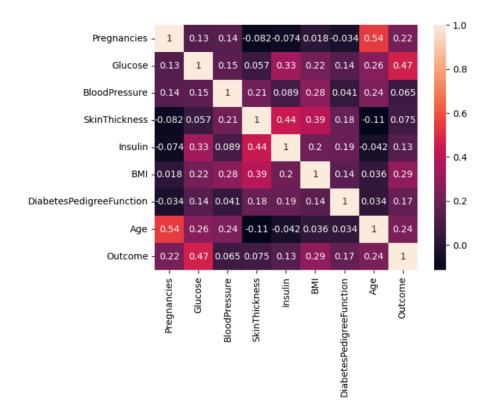
sns.scatterplot(x='Age', y='Insulin', hue='Outcome', data=df,)
plt.legend(bbox_to_anchor=(1, 1), loc=2)
plt.show()



sns.pairplot(df.drop(['BMI'], axis = 1), hue='Outcome', height=2)



sns.heatmap(df.corr(method='pearson'), annot = True);
plt.show()



RESULT:

Thus, Visualization has been performed on both iris and diabetes dataset using matplotlib and seaborn libraries.