Name- Kshitij V Darwhekar

Roll No - TETB19

Sub: Soft Computitng

Batch -B2

Experiment 3: Implementation of Decision Tree, Random Forest, KNN, Naïve Bayes with hyperparameter tunning.

1. DECISION TREE

import pandas as pd
from google.colab import drive
drive.mount('/content/drive')

Mounted at /content/drive

df = pd.read_csv("/content/drive/MyDrive/ML/Titanic-Dataset.csv")
df.head()

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs	female	38.0	1	0	PC 17599	71.

df.drop(['PassengerId','Name','SibSp','Parch','Ticket','Cabin','Embarked'],axis='columns',

df.head()

		Survived	Pclass	Sex	Age	Fare	77
_	0	0	3	male	22.0	7.2500	
	1	1	1	female	38.0	71.2833	
	2	1	3	female	26.0	7.9250	
		<pre>df.drop(' df.Surviv</pre>		d',axis=	'colum	nns')	
	-	J	J	IIIGIO	00.0	0.0000	

inputs.Sex = inputs.Sex.map({'male': 1, 'female': 2})

```
inputs.Age[:10]
```

```
0
    22.0
    38.0
1
2
    26.0
3
    35.0
4
    35.0
5
    NaN
6
     54.0
7
    2.0
8
    27.0
9
    14.0
```

Name: Age, dtype: float64

inputs.Age = inputs.Age.fillna(inputs.Age.mean())

inputs.head()

1	Fare	Age	Sex	Pclass	
	7.2500	22.0	1	3	0
	71.2833	38.0	2	1	1
	7.9250	26.0	2	3	2
	53.1000	35.0	2	1	3
	8.0500	35.0	1	3	4

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(inputs,target,test_size=0.2)

len(X_train)

712

len(X_test)

```
from sklearn import tree
model = tree.DecisionTreeClassifier()

model.fit(X_train,y_train)
    DecisionTreeClassifier()

model.score(X_test,y_test)
    0.7877094972067039
```

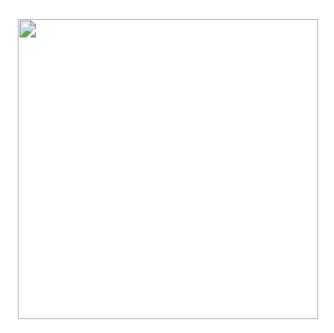
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2. KNN (K Nearest Neighbors) Classification

```
import pandas as pd
from sklearn.datasets import load_iris
iris = load_iris()
```



```
iris.feature_names

['sepal length (cm)',
    'sepal width (cm)',
    'petal length (cm)',
    'petal width (cm)']

iris.target_names

    array(['setosa', 'versicolor', 'virginica'], dtype='<U10')

df = pd.DataFrame(iris.data,columns=iris.feature_names)
df.head()</pre>
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
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
2	1.6	0.4	1.5	0.0

df['target'] = iris.target
df.head()

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
0	5.1	3.5	1.4	0.2	0
1	4.9	3.0	1.4	0.2	0
2	4.7	3.2	1.3	0.2	0
3	4.6	3.1	1.5	0.2	0
4	5.0	3.6	1.4	0.2	0

df[df.target==1].head()

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
50	7.0	3.2	4.7	1.4	1
51	6.4	3.2	4.5	1.5	1
52	6.9	3.1	4.9	1.5	1
53	5.5	2.3	4.0	1.3	1
54	6.5	2.8	4.6	1.5	1

df[df.target==2].head()

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
100	6.3	3.3	6.0	2.5	2
101	5.8	2.7	5.1	1.9	2
102	7.1	3.0	5.9	2.1	2
103	6.3	2.9	5.6	1.8	2
104	6.5	3.0	5.8	2.2	2

df['flower_name'] =df.target.apply(lambda x: iris.target_names[x])
df.head()

		sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target	flower_name
	0	5.1	3.5	1.4	0.2	0	setosa
	1	4.9	3.0	1.4	0.2	0	setosa
	2	4.7	3.2	1.3	0.2	0	setosa
	3	4.6	3.1	1.5	0.2	0	setosa
df[45	:55]						
		sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target	flower_name
	45	4.8	3.0	1.4	0.3	0	setosa
	46	5.1	3.8	1.6	0.2	0	setosa
	47	4.6	3.2	1.4	0.2	0	setosa
	48	5.3	3.7	1.5	0.2	0	setosa
	49	5.0	3.3	1.4	0.2	0	setosa
	50	7.0	3.2	4.7	1.4	1	versicolor
	51	6.4	3.2	4.5	1.5	1	versicolor
	52	6.9	3.1	4.9	1.5	1	versicolor
	53	5.5	2.3	4.0	1.3	1	versicolor
	54	6.5	2.8	4.6	1.5	1	versicolor

sepal length sepal width petal length petal width

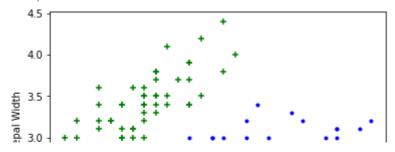
df0 = df[:50]df1 = df[50:100]df2 = df[100:]

import matplotlib.pyplot as plt %matplotlib inline

Sepal length vs Sepal Width (Setosa vs Versicolor)

```
plt.xlabel('Sepal Length')
plt.ylabel('Sepal Width')
plt.scatter(df0['sepal length (cm)'], df0['sepal width (cm)'],color="green",marker='+')
plt.scatter(df1['sepal length (cm)'], df1['sepal width (cm)'],color="blue",marker='.')
```

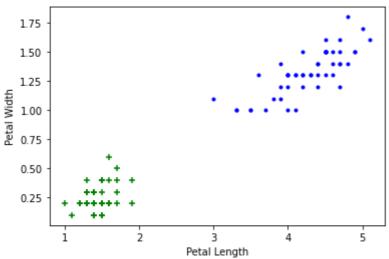
<matplotlib.collections.PathCollection at 0x7f8d07945f50>



Petal length vs Pepal Width (Setosa vs Versicolor)

```
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
plt.scatter(df0['petal length (cm)'], df0['petal width (cm)'],color="green",marker='+')
plt.scatter(df1['petal length (cm)'], df1['petal width (cm)'],color="blue",marker='.')
```

<matplotlib.collections.PathCollection at 0x7f8d07437910>



Train test split

30

Create KNN (K Neighrest Neighbour Classifier)

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=10)

knn.fit(X_train, y_train)
    KNeighborsClassifier(n_neighbors=10)

knn.score(X_test, y_test)
    0.96666666666667

knn.predict([[4.8,3.0,1.5,0.3]])
    /usr/local/lib/python3.7/dist-packages/sklearn/base.py:451: UserWarning: X does not h
    "X does not have valid feature names, but"
    array([0])
```

Plot Confusion Matrix

Text(42.0, 0.5, 'Truth')



Print classification report for precesion, recall and f1-score for each classes



from sklearn.metrics import classification_report

print(classification_report(y_test, y_pred))

	precision	recall	f1-score	support
0	1.00	1.00	1.00	11
1	1.00	0.92	0.96	13
2	0.86	1.00	0.92	6
accuracy			0.97	30
macro avg	0.95	0.97	0.96	30
weighted avg	0.97	0.97	0.97	30

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3. RANDOM FOREST

```
import pandas as pd
from sklearn.datasets import load_digits
digits = load_digits()

dir(digits)

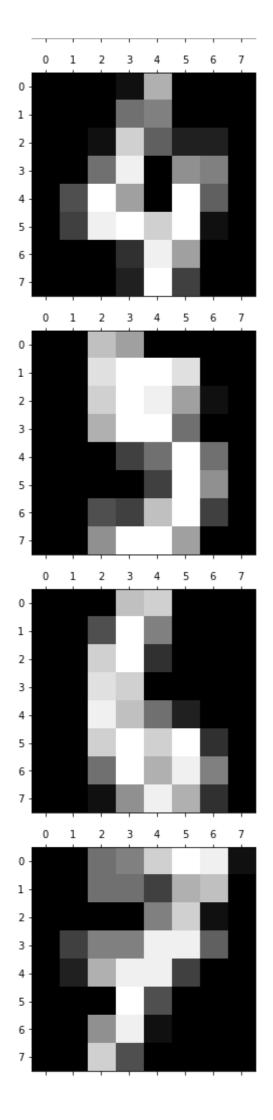
   ['DESCR', 'data', 'feature_names', 'frame', 'images', 'target', 'target_names']

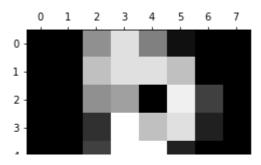
%matplotlib inline
import matplotlib.pyplot as plt

plt.gray()
for i in range(10):
   plt.matshow(digits.images[i])
```

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df = pd.DataFrame(digits.data)
df.head()

	0	1	2	3	4	5	6	7	8	9	 54	55	56	57	58	59	
0	0.0	0.0	5.0	13.0	9.0	1.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	6.0	13.0	1
1	0.0	0.0	0.0	12.0	13.0	5.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	11.0	1
2	0.0	0.0	0.0	4.0	15.0	12.0	0.0	0.0	0.0	0.0	 5.0	0.0	0.0	0.0	0.0	3.0	1
3	0.0	0.0	7.0	15.0	13.0	1.0	0.0	0.0	0.0	8.0	 9.0	0.0	0.0	0.0	7.0	13.0	1
4	0.0	0.0	0.0	1.0	11.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	2.0	1

5 rows × 64 columns

df['target'] = digits.target

df[0:12]

	0	1	2	3	4	5	6	7	8	9	 55	56	57	58	59	
0	0.0	0.0	5.0	13.0	9.0	1.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	6.0	13.0	1
1	0.0	0.0	0.0	12.0	13.0	5.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	11.0	1
2	0.0	0.0	0.0	4.0	15.0	12.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	3.0	1
3	0.0	0.0	7.0	15.0	13.0	1.0	0.0	0.0	0.0	8.0	 0.0	0.0	0.0	7.0	13.0	1
4	0.0	0.0	0.0	1.0	11.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	2.0	1
5	0.0	0.0	12.0	10.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	9.0	16.0	1
6	0.0	0.0	0.0	12.0	13.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	1.0	9.0	1
7	0.0	0.0	7.0	8.0	13.0	16.0	15.0	1.0	0.0	0.0	 0.0	0.0	0.0	13.0	5.0	
8	0.0	0.0	9.0	14.0	8.0	1.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	11.0	16.0	1
9	0.0	0.0	11.0	12.0	0.0	0.0	0.0	0.0	0.0	2.0	 0.0	0.0	0.0	9.0	12.0	1
10	0.0	0.0	1.0	9.0	15.0	11.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	1.0	10.0	1
11	0.0	0.0	0.0	0.0	14.0	13.0	1.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	1.0	1

12 rows × 65 columns

```
X = df.drop('target',axis = 'columns')
y = df.target
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.1)
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier(n estimators=30)
model.fit(X_train, y_train)
    RandomForestClassifier(n estimators=30)
model.score(X_test, y_test)
    0.95
y_predicted = model.predict(X_test)
from sklearn.datasets import make_classification
## Confusion Matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_predicted)
cm
    array([[18, 0, 0, 0, 0, 0, 0, 0, 0],
           [ 0, 17, 0, 0, 0, 0, 0, 0,
                                              0],
           [ 0, 0, 15, 0, 0, 0, 0, 0, 0,
                                             0],
           [0, 0, 0, 25, 0, 0, 0, 0, 0],
           [0, 0, 0, 0, 15, 0, 0, 0, 0,
                                              01,
           [ 0, 0, 0, 0, 1, 18, 1, 0, 0,
                                             1],
           [ 0, 0, 0, 0, 0, 18, 0, 0,
                                              01,
           [ 0, 0, 0, 0, 0, 0, 15, 0,
           [ 0, 0, 1, 2, 0, 0, 0, 0, 14,
           [0, 1, 0, 0, 0, 1, 0, 0, 1, 16]]
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sn
plt.figure(figsize=(10,7))
```

sn.heatmap(cm, annot=True)
plt.xlabel('Predicted')
plt.ylabel('Truth')

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4. NAIVE BAYES

	precision	recall	f1-score	support
0	0.99	0.99 0.85	0.99	178 182
2	0.98	0.64	0.77	177
3	0.94	0.79	0.86	183
4	0.98	0.84	0.90	181
5	0.91	0.93	0.92	182
6	0.96	0.99	0.98	181
7	0.72	0.99	0.83	179
8	0.58	0.86	0.69	174
9	0.94	0.71	0.81	180

accuracy macro avg weighted avg					0.8			0.86 0.86		0.86 0.86 0.86	1797 1797 1797
[[1	76	0	0	0	1	0	0	1	0	0]	
[0	154	0	0	0	0	3	5	14	6]	
[0	13	113	0	0	1	1	0	49	0]	
[0	2	2	145	0	6	0	7	20	1]	
[1	1	0	0	152	1	2	21	3	0]	
[0	0	0	3	0	169	1	6	2	1]	
[0	1	0	0	0	1	179	0	0	0]	
[0	0	0	0	1	1	0	177	0	0]	
[0	8	0	1	0	3	0	12	150	0]	
[1	6	0	5	1	3	0	17	20	127]]	

Multinomial Naive Bayes

from sklearn.naive_bayes import MultinomialNB
model = MultinomialNB()

model.fit(dataset.data, dataset.target)
expected = dataset.target
predicted = model.predict(dataset.data)
print(metrics.classification_report(expected, predicted))
print(metrics.confusion_matrix(expected, predicted))

	precision			on	recall f1-scor				support	
0			0.99				9.98		0.99	178
	1			0.87			9.75		0.81	182
		2	0.90			0.90			0.90	177
	3			0.99			0.87		0.93	183
	4			0.96			9.96		0.96	181
		5	0.97			(0.86		0.91	182
		6		0.98			0.97		0.98	181
		7		0.89			0.99		0.94	179
		8		0.78			0.89		0.83	174
		9		0.76			0.88		0.82	180
а	nccura	асу							0.91	1797
	icro a	_		0.9	91	(0.91		0.91	1797
weighted avg				0.9	91	(0.91		0.91	1797
[[175	0	0	0	3	0	0	0	0	0]	
[6	137	14	0	0	1	2	0	13	15]	
[6	7	160	0	0	0	0	0	8	2]	
[6	0	2	159	0	2	0	5	8	7]	
[1	. 0	0	0	173	0	0	4	3	0]	
[6		0	0	1	157	1	1	2	20]	
[6		0	0	1	1	176	0	1	0]	
[6		0	0	0	0	0	178	1	0]	
[6		1	0	1	0	1	1		5]	
[6		0	1	1	1	0	11	7		
L	_	0	_	_	_	0		,		

```
model = BernoulliNB()
model.fit(dataset.data, dataset.target)
expected = dataset.target
predicted = model.predict(dataset.data)
print(metrics.classification_report(expected, predicted))
print(metrics.confusion_matrix(expected, predicted))
                    precision recall f1-score support
                         0.98
                                 0.98
                                             0.98
                                                         178

      0.76
      0.62

      0.86
      0.86

      0.91
      0.86

      0.91
      0.95

      0.93
      0.82

                1
                                              0.68
                                                         182
                2
                                                         177
                                             0.86
                                                        183
                3
                                            0.88
                                           0.93
                4
                                                         181
                5
                                            0.87
                                                         182
                6
                       0.97
                                 0.94
                                            0.96
                                                        181

      0.88
      0.98
      0.93

      0.70
      0.82
      0.75

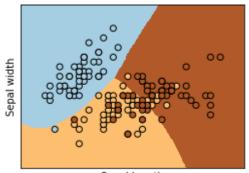
      0.76
      0.81
      0.78

                7
                                                         179
                8
                                                         174
                                                        180
                                             0.86
         accuracy
                                                    1797
                       0.87
                                 0.86
                                             0.86
                                                       1797
        macro avg
                        0.87
                                  0.86
                                              0.86
                                                       1797
     weighted avg
     [[175 1
                    0 2
                                              0]
      [ 0 112 21
                    0 3 1 1 1 32 11]
         0
            6 153 6
                          0 0 0 1 11
                                               0]
        1 1 3 157 0 2 0 3 7
                                             91
      [ 0 1 0 0 172 0 0 7 1
                                             0]
        2 3
                0 2 1 149 2 0 3 20]
        0 5 0 0 2 2 171 0 1 0]
        0 0 0 0 3 0 0 175 1
                                               0]
         0 13 1 4 0 3 2 2 142
                                               71
        0 6 0 3 7 3 0 9
                                           6 146]]
##
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
def Naive_bayes(Model_Type):
        # import some data to play with
        iris = datasets.load iris()
        X = iris.data[:, :2] # we only take the first two features.
        Y = iris.target
        h = .02 # step size in the mesh
        # we create an instance of Neighbours Classifier and fit the data.
        if(Model_Type=='Gaussian'):
            model = GaussianNB()
        elif (Model Type=='Multinomial'):
                model = MultinomialNB()
        else:
```

model = BernoulliNB()

from sklearn.naive_bayes import BernoulliNB

```
model.fit(X, Y)
        # Plot the decision boundary. For that, we will assign a color to each
        # point in the mesh [x_min, m_max]x[y_min, y_max].
        x_{min}, x_{max} = X[:, 0].min() - .5, X[:, 0].max() + .5
        y_{min}, y_{max} = X[:, 1].min() - .5, X[:, 1].max() + .5
        xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
        Z = model.predict(np.c_[xx.ravel(), yy.ravel()])
        # Put the result into a color plot
        Z = Z.reshape(xx.shape)
        plt.figure(1, figsize=(4, 3))
        plt.pcolormesh(xx, yy, Z, cmap=plt.cm.Paired)
        # Plot also the training points
        plt.scatter(X[:, 0], X[:, 1], c=Y, edgecolors='k', cmap=plt.cm.Paired)
        plt.xlabel('Sepal length')
        plt.ylabel('Sepal width')
        plt.xlim(xx.min(), xx.max())
        plt.ylim(yy.min(), yy.max())
        plt.xticks(())
        plt.yticks(())
        plt.show()
        model.fit(dataset.data, dataset.target)
        expected = dataset.target
        predicted = model.predict(dataset.data)
        print(metrics.classification_report(expected, predicted))
        print(metrics.confusion_matrix(expected, predicted))
from IPython.html import widgets
from IPython.html.widgets import interact
from IPython.display import display
import warnings
warnings.filterwarnings('ignore')
i = interact(Naive bayes, Model Type=['Gaussian','Multinomial','Bernoulli'])
```



Se	pal	ler	١q	tŀ	٦

Sepai leligili									
pre				on	red	call	f1	-score	support
0				99	(0.99		0.99	178
1			0.8	33	(0.85		0.84	182
2			0.9	98	(0.64		0.77	177
3			0.9	94	(3.79		0.86	183
4			0.9	98	(0.84		0.90	181
5			0.9	91	(9.93		0.92	182
	6		0.9	96	(0.99		0.98	181
	7		0.7	72	(3.99		0.83	179
	8		0.5	58	(0.86		0.69	174
accuracy macro avg weighted avg				0.88 0.89				0.86 0.86	1/9/ 1797 1797
0	0	0	1	0	0	1	0	0]	
								_	
								_	
								_	
								_	
								_	
								_	
								_	
								_	
6	0	5	1	3	0	17	20	127]]	
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