Name : Kshitij V Darwhekar

Roll No: TETB19

Sub: Soft Computitng

Batch: B2

Experiment 1 : Experimental Data Analysis: Perform following operations on any open dataset available in Python/Kaggle

```
import numpy as np
import pandas as pd
```

```
from google.colab import drive
drive.mount('/content/drive/')
```

```
#data = open('ML/penguins_size','r')
```

```
Mounted at /content/drive/
```

```
database = pd.read_csv('/content/drive/MyDrive/ML/penguins_size.csv')
```

```
database.head()
```

	species	island	culmen_length_mm	culmen_depth_mm	flipper_length_mm	body_mas
0	Adelie	Torgersen	39.1	18.7	181.0	375
1	Adelie	Torgersen	39.5	17.4	186.0	380
2	Adelie	Torgersen	40.3	18.0	195.0	325
3	Adelie	Torgersen	NaN	NaN	NaN	N
4	Adelie	Torgersen	36.7	19.3	193.0	345

```
database.head(10)
```

	species	island	culmen_length_mm	culmen_depth_mm	flipper_length_mm	body_mas
0	Adelie	Torgersen	39.1	18.7	181.0	375
1	Adelie	Torgersen	39.5	17.4	186.0	380
2	Adelie	Torgersen	40.3	18.0	195.0	325
3	Adelie	Torgersen	NaN	NaN	NaN	N
4	Adelie	Torgersen	36.7	19.3	193.0	345
5	Adelie	Torgersen	39.3	20.6	190.0	365
6	Adelie	Torgersen	38.9	17.8	181.0	362

```
database.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 344 entries, 0 to 343
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   species            344 non-null    object 
 1   island             344 non-null    object 
 2   culmen_length_mm   342 non-null    float64
 3   culmen_depth_mm    342 non-null    float64
 4   flipper_length_mm  342 non-null    float64
 5   body_mass_g        342 non-null    float64
 6   sex                334 non-null    object 
dtypes: float64(4), object(3)
memory usage: 18.9+ KB
```

```
print(database.isnull().sum())
```

```
species               0
island                0
culmen_length_mm      2
culmen_depth_mm       2
flipper_length_mm     2
body_mass_g           2
sex                  10
dtype: int64
```

```
database = database.dropna()
database.head()
```

	species	island	culmen_length_mm	culmen_depth_mm	flipper_length_mm	body_mas
0	Adelie	Torgersen	39.1	18.7	181.0	375
1	Adelie	Torgersen	39.5	17.4	186.0	380
2	Adelie	Torgersen	40.3	18.0	195.0	325
4	Adelie	Torgersen	36.7	19.3	193.0	345
5	Adelie	Torgersen	39.3	20.6	190.0	365

```
len(database)
```

```
334
```

```
len(database.columns)
```

```
7
```

```
database.loc[(database['sex'] != 'FEMALE')& (database['sex'] != 'MALE')]
```

	species	island	culmen_length_mm	culmen_depth_mm	flipper_length_mm	body_mas
336	Gentoo	Biscoe	44.5	15.7	217.0	487

```
database['culmen_depth_mm'].fillna((database['culmen_depth_mm'].mean()), inplace=True)
database['flipper_length_mm'].fillna((database['flipper_length_mm'].mean()), inplace=True)
database['body_mass_g'].fillna((database['body_mass_g'].mean()), inplace=True)
database['culmen_length_mm'].fillna((database['culmen_length_mm'].mean()), inplace=True)
database['sex'].fillna((database['sex'].value_counts().index[0]), inplace=True)

database.reset_index()
database.head()
```

	species	island	culmen_length_mm	culmen_depth_mm	flipper_length_mm	body_mas
0	Adelie	Torgersen	39.1	18.7	181.0	375
1	Adelie	Torgersen	39.5	17.4	186.0	380
2	Adelie	Torgersen	40.3	18.0	195.0	325
4	Adelie	Torgersen	36.7	19.3	193.0	345
5	Adelie	Torgersen	39.3	20.6	190.0	365

```
col_new = ['new_species','new_island','new_culmen_length_mm','new_culmen_depth_mm','new_fl
database.columns = col_new
col_new
```

```
['new_species',
 'new_island',
 'new_culmen_length_mm',
 'new_culmen_depth_mm',
 'new_flipper_length',
 'new_body_mass_g',
 'new_sex']
```

```
database.head()
```

	new_species	new_island	new_culmen_length_mm	new_culmen_depth_mm	new_flipper_l
0	Adelie	Torgersen	39.1	18.7	
1	Adelie	Torgersen	39.5	17.4	
2	Adelie	Torgersen	40.3	18.0	

```
database_new = database.drop(['new_island','new_culmen_length_mm','new_flipper_length'],ax
database.head()
```

	new_species	new_island	new_culmen_length_mm	new_culmen_depth_mm	new_flipper_l
0	Adelie	Torgersen	39.1	18.7	
1	Adelie	Torgersen	39.5	17.4	
2	Adelie	Torgersen	40.3	18.0	
4	Adelie	Torgersen	36.7	19.3	
5	Adelie	Torgersen	39.3	20.6	

```
database_new.head()
```

	new_species	new_culmen_depth_mm	new_body_mass_g	new_sex
0	Adelie	18.7	3750.0	MALE
1	Adelie	17.4	3800.0	FEMALE
2	Adelie	18.0	3250.0	FEMALE
4	Adelie	19.3	3450.0	FEMALE
5	Adelie	20.6	3650.0	MALE

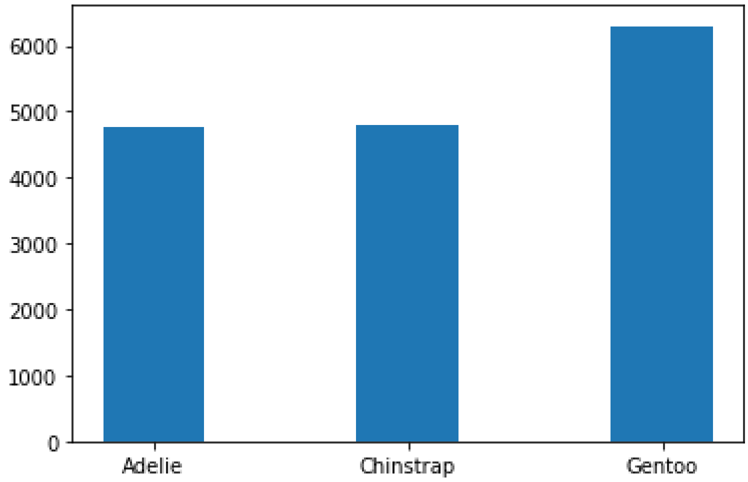
```
database_new["islands"] = "Torgersen"
database_new.head()
```

	new_species	new_culmen_depth_mm	new_body_mass_g	new_sex	islands
0	Adelie	18.7	3750.0	MALE	Torgersen
1	Adelie	17.4	3800.0	FEMALE	Torgersen
2	Adelie	18.0	3250.0	FEMALE	Torgersen
4	Adelie	19.3	3450.0	FEMALE	Torgersen
5	Adelie	20.6	3650.0	MALE	Torgersen

```
import matplotlib.pyplot as plt
import seaborn as sns
```

```
X = database['new_species']
Y = database['new_body_mass_g']
plt.bar(X,Y,width = 0.4)
```

```
<BarContainer object of 334 artists>
```



+ Code   + Text

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Batch: B2

Experiment 2: Liner Regression and Logistic Regression Model Implementation on Given Dataset.

```
import matplotlib.pyplot as plt
import seaborn as sns
import·pandas·as·pd
import·numpy·as·np
```

```
from google.colab import drive
drive.mount('/content/drive/')
```

```
Mounted at /content/drive/
```

```
pf = pd.read_csv("/content/drive/MyDrive/ML/heart.csv")
```

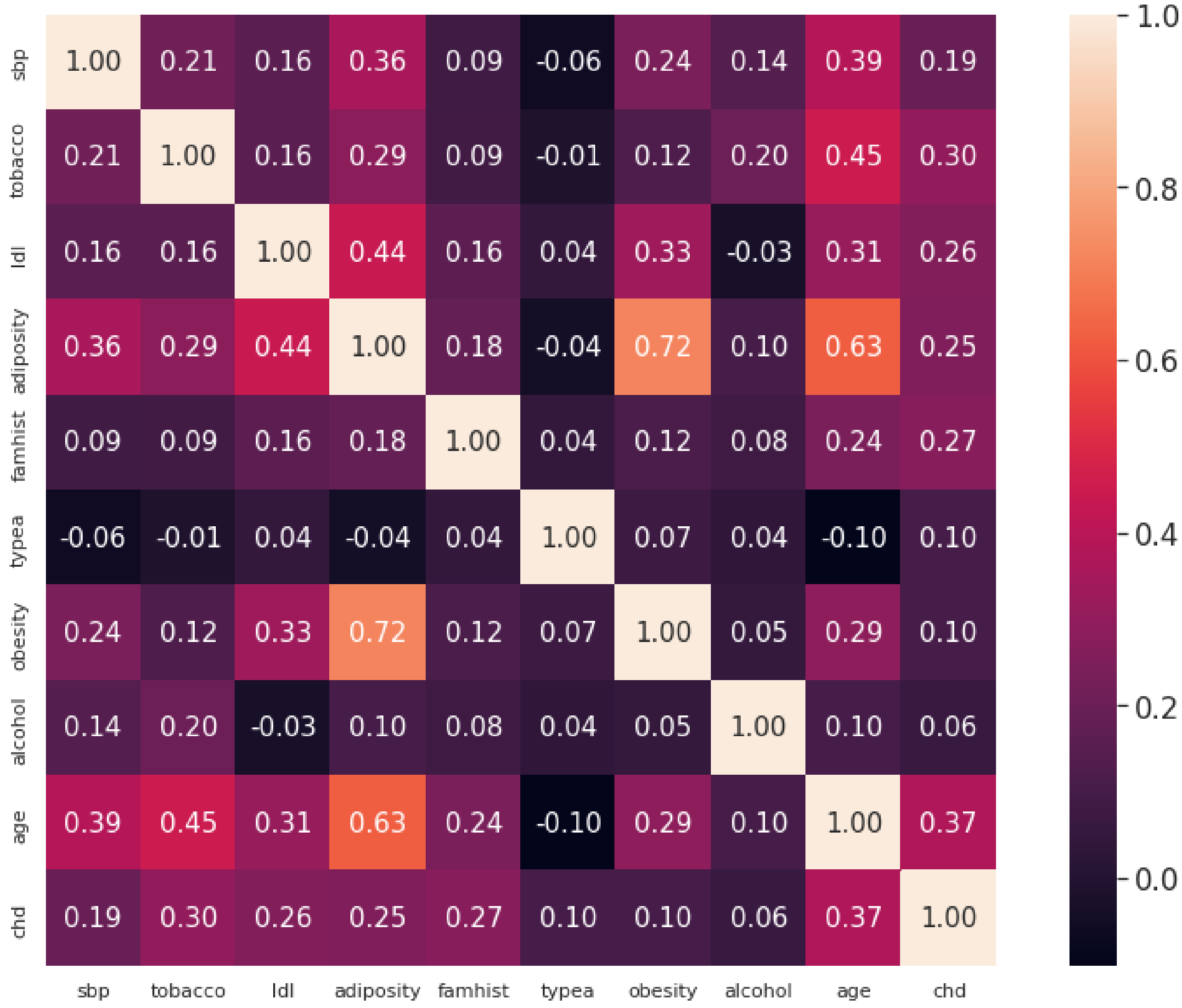
```
pf.head()
```

	sbp	tobacco	ldl	adiposity	famhist	typea	obesity	alcohol	age	chd
0	160	12.00	5.73	23.11	Present	49	25.30	97.20	52	1
1	144	0.01	4.41	28.61	Absent	55	28.87	2.06	63	1
2	118	0.08	3.48	32.28	Present	52	29.14	3.81	46	0
3	170	7.50	6.41	38.03	Present	51	31.99	24.26	58	1
4	134	13.60	3.50	27.78	Present	60	25.99	57.34	49	1

```
history_mapping = {'Absent': 0,'Present': 1}
pf["famhist"] = pf["famhist"].map(history_mapping)
pf.head()
```

	sbp	tobacco	ldl	adiposity	famhist	typea	obesity	alcohol	age	chd
0	160	12.00	5.73	23.11	1	49	25.30	97.20	52	1
1	144	0.01	4.41	28.61	0	55	28.87	2.06	63	1
2	118	0.08	3.48	32.28	1	52	29.14	3.81	46	0

```
sns.set(style='whitegrid', context='notebook')
cols = ['sbp','tobacco','ldl','adiposity','famhist','typea','obesity', 'alcohol','age', 'c
f, ax = plt.subplots(figsize=(15, 10))
cm = np.corrcoef(pf[cols].values.T)
sns.set(font_scale=1.5)
hm = sns.heatmap(cm,
                 cbar=True,
                 annot=True,
                 square=True,
                 fmt='.2f',
                 annot_kws={'size': 15},
                 yticklabels=cols,
                 xticklabels=cols)

plt.show()
```



```
X = pf[['tobacco','ldl','adiposity','famhist','typea','obesity','alcohol','age']].values
y = pf[['chd']].values


from sklearn.model_selection import train_test_split


X_train , X_test , y_train,y_test = train_test_split(X,y,train_size = 0.9)


# Apply logistic regression

from sklearn.linear_model import LogisticRegression


model = LogisticRegression(C=1,penalty='l2')
model.fit(X_train,y_train)
y_pred=model.predict(X_test)
```

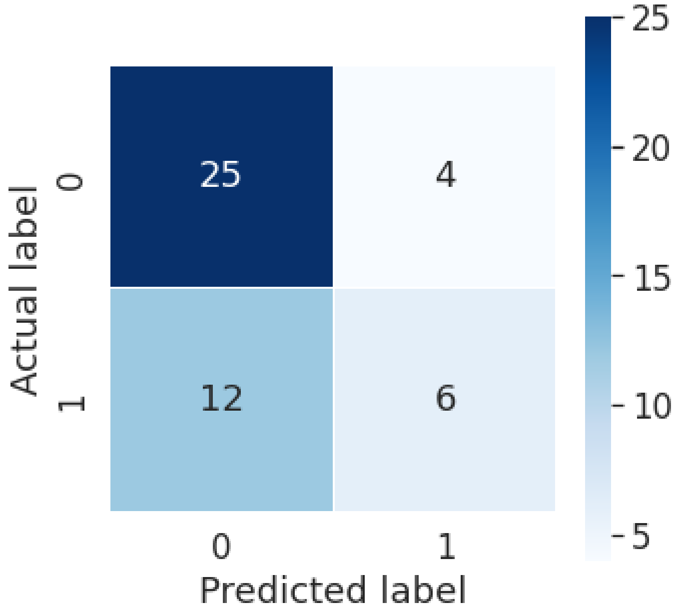
```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:993: DataConversic
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic.py:818: Converg
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
```

```
print ('Training Accuracy: %.2f' % model.score(X_train,y_train))

print ('Test Accuracy: %.2f' % model.score(X_test,y_test))
```

```
Training Accuracy: 0.74
Test Accuracy: 0.66
```

```
import seaborn as sns
from sklearn.tree import plot_tree
from sklearn import tree
from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test,y_pred)
plt.figure(figsize=(5,5))
sns.heatmap(data=cm,linewidths=.5, annot=True,square =True, cmap ='Blues')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

```
Text(0.5, 37.79999999999998, 'Predicted label')
```



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Name- Kshitij V Darwhekar

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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 Th	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
0	0	3	male	22.0	7.2500
1	1	1	female	38.0	71.2833
2	1	3	female	26.0	7.9250

```
inputs = df.drop('Survived',axis='columns')
target = df.Survived
```

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

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

```
0    22.0
1    38.0
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()
```

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

```
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)
```

```
179
```

```
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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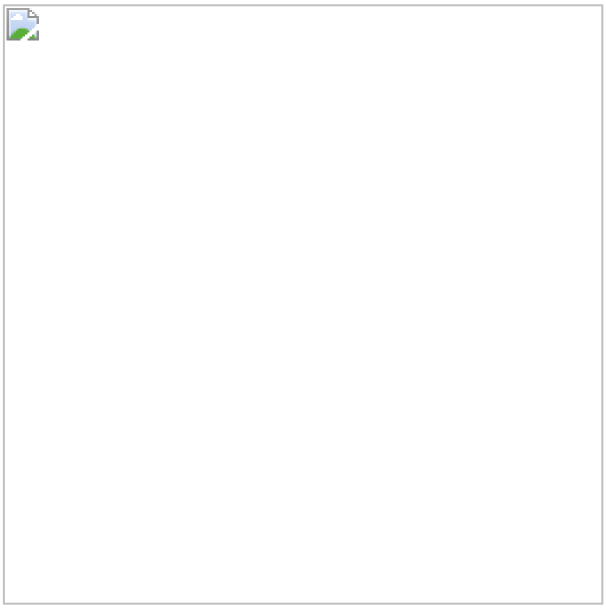
Batch -B2

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()
```

	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
3	4.6	3.1	1.5	0.2

```
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

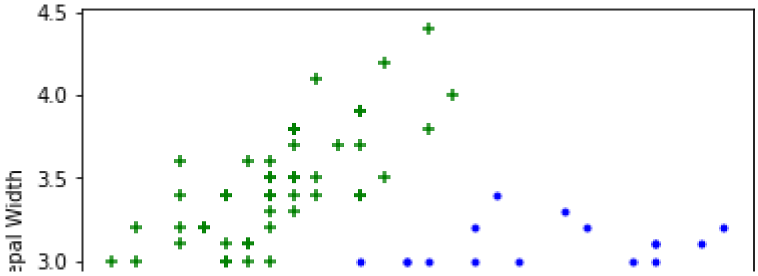
```
df0 = df[:50]
df1 = df[50:100]
df2 = df[100:]
```

```
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='.')
```

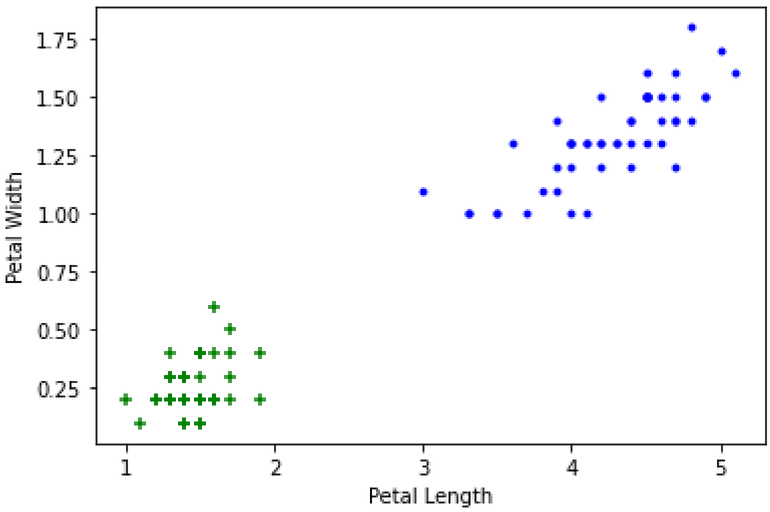
<matplotlib.collections.PathCollection at 0x7f8d07945f50>



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

```
from sklearn.model_selection import train_test_split
```

```
X = df.drop(['target','flower_name'], axis='columns')
y = df.target
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)
```

```
len(X_train)
```

    120

```
len(X_test)
```

    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)
```

```
0.9666666666666667
```

```
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

```
from sklearn.metrics import confusion_matrix
y_pred = knn.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
cm
```

```
array([[11,  0,  0],
       [ 0, 12,  1],
       [ 0,  0,  6]])
```

```
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sn
plt.figure(figsize=(7,5))
sn.heatmap(cm, annot=True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

```
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()
```

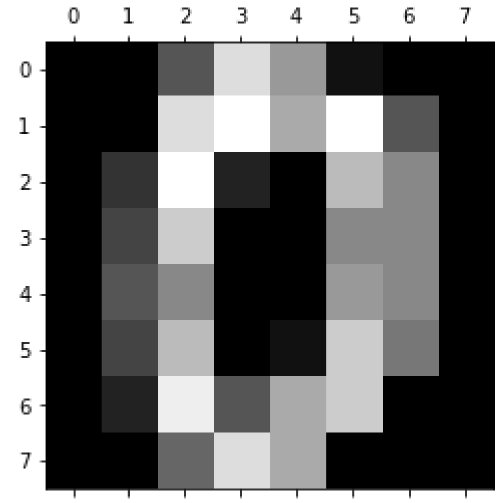
```
dir(digits)
```

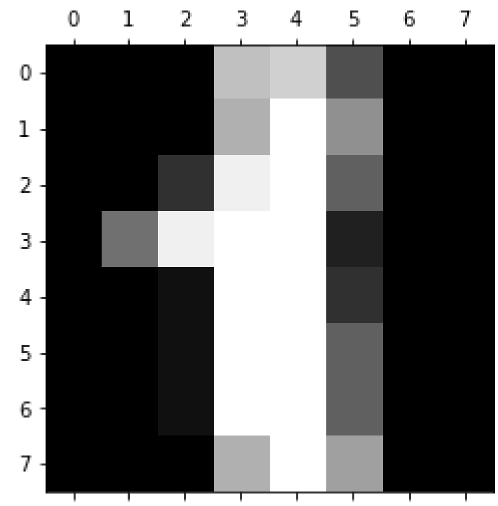
```
['DESCR', 'data', 'feature_names', 'frame', 'images', 'target', 'target_names']
```

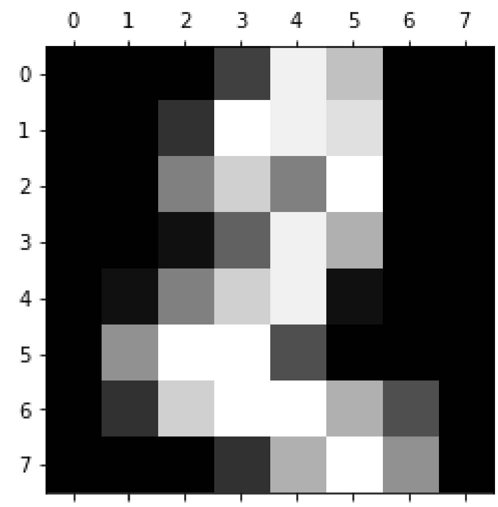
```
%matplotlib inline
import matplotlib.pyplot as plt
```

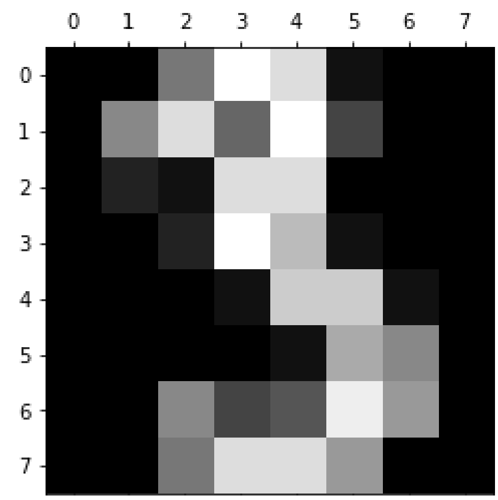
```
plt.gray()
for i in range(10):
  plt.matshow(digits.images[i])
```

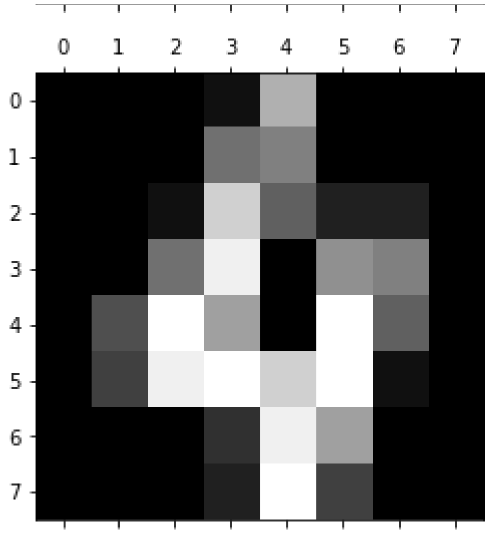
<Figure size 432x288 with 0 Axes>

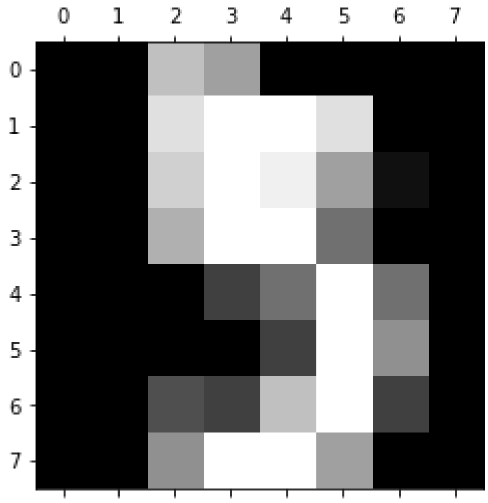


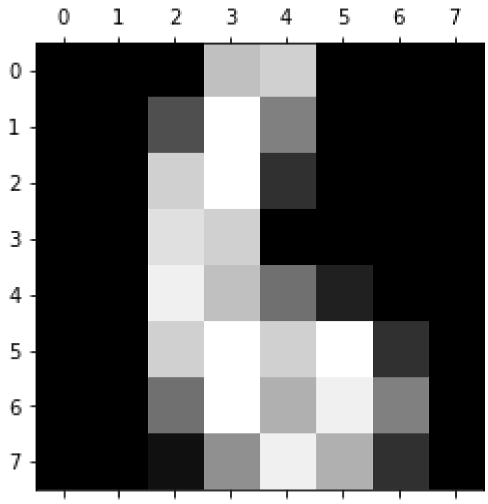


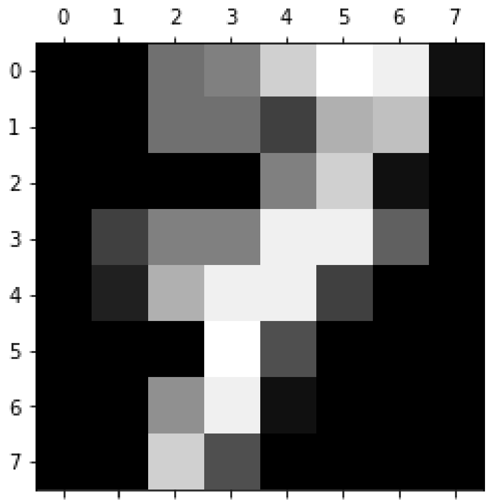


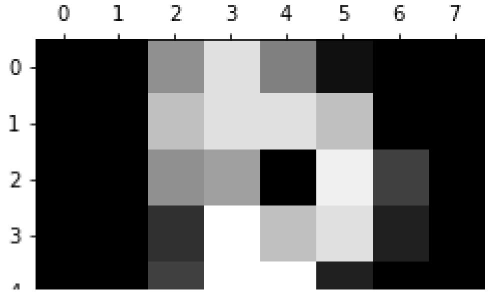



0 1 2 3 4 5 6 7
0 1 2 3 4 5 6 7


0 1 2 3 4 5 6 7
0 1 2 3 4 5 6 7


0 1 2 3 4 5 6 7
0 1 2 3 4 5 6 7


0 1 2 3 4 5 6 7
0 1 2 3 4 5 6 7



```
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

```
## Train the model and prediction
```

```
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],
           [ 0, 17,  0,  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,  0, 15,  0,  0,  0,  0,  0],
           [ 0,  0,  0,  0,  1, 18,  1,  0,  0,  1],
           [ 0,  0,  0,  0,  0,  0, 18,  0,  0,  0],
           [ 0,  0,  0,  0,  0,  0,  0, 15,  0,  0],
           [ 0,  0,  1,  2,  0,  0,  0,  0, 14,  0],
           [ 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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Batch: B2

4. NAIVE BAYES

```
import warnings
warnings.filterwarnings('ignore')
```

```
from sklearn import datasets
from sklearn import metrics
from sklearn.naive_bayes import GaussianNB
```

```
from sklearn.datasets import load_digits
dataset = load_digits()
```

```
model = GaussianNB()
model.fit(dataset.data, dataset.target)
```

```
    GaussianNB()
```

```
## Predictions
```

```
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       0.99      0.99      0.99       178
           1       0.83      0.85      0.84       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                           0.86      1797
   macro avg       0.88      0.86      0.86      1797
weighted avg       0.89      0.86      0.86      1797

[[176   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))
```

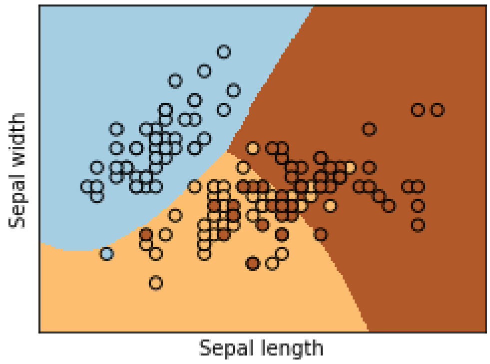
```
              precision    recall  f1-score   support

           0       0.99      0.98      0.99       178
           1       0.87      0.75      0.81       182
           2       0.90      0.90      0.90       177
           3       0.99      0.87      0.93       183
           4       0.96      0.96      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

    accuracy                           0.91      1797
   macro avg       0.91      0.91      0.91      1797
weighted avg       0.91      0.91      0.91      1797

[[175   0   0   0   3   0   0   0   0   0]
 [  0 137  14   0   0   1   2   0  13  15]
 [  0   7 160   0   0   0   0   0   8   2]
 [  0   0   2 159   0   2   0   5   8   7]
 [  1   0   0   0 173   0   0   4   3   0]
 [  0   0   0   0   1 157   1   1   2  20]
 [  0   2   0   0   1   1 176   0   1   0]
 [  0   0   0   0   0   0   0 178   1   0]
 [  0  11   1   0   1   0   1   1 154   5]
 [  0   1   0   1   1   1   0  11   7 158]]
```

```
## Bernoulli Naive bayes
```

```
from sklearn.naive_bayes import BernoulliNB
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       0.98      0.98      0.98       178
                1       0.76      0.62      0.68       182
                2       0.86      0.86      0.86       177
                3       0.91      0.86      0.88       183
                4       0.91      0.95      0.93       181
                5       0.93      0.82      0.87       182
                6       0.97      0.94      0.96       181
                7       0.88      0.98      0.93       179
                8       0.70      0.82      0.75       174
                9       0.76      0.81      0.78       180

         accuracy                           0.86      1797
        macro avg       0.87      0.86      0.86      1797
     weighted avg       0.87      0.86      0.86      1797

     [[175   1   0   0   2   0   0   0   0   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   9]
      [  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   7]
      [  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()
```

```
        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'])
```

Model_Type Gaussian




```
              precision    recall  f1-score   support

           0       0.99      0.99      0.99       178
           1       0.83      0.85      0.84       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


    accuracy                           0.86      1797
   macro avg       0.88      0.86      0.86      1797
weighted avg       0.89      0.86      0.86      1797

[[176   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]]
```

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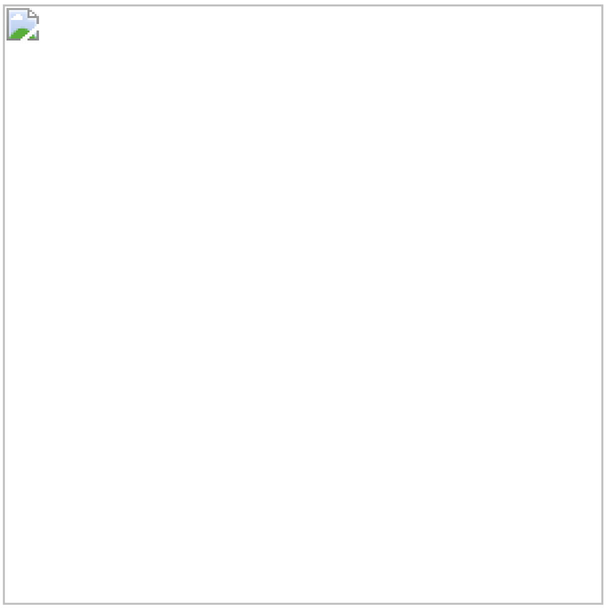
Experiment 4: Machine Learning for Image Classification (Support Vector Machine Tutorial Using Python Sklearn)

```
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()
```

	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
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

```
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

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
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

```
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
4	5.0	3.6	1.4	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

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

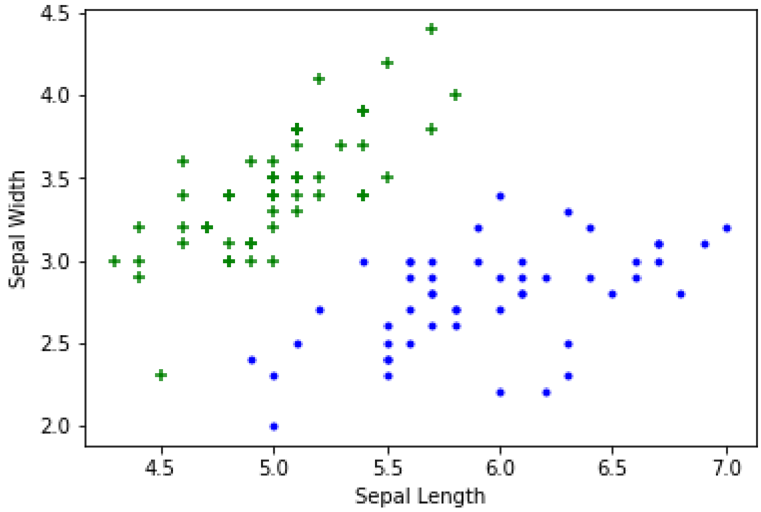
```
import matplotlib.pyplot as plt
%matplotlib inline
```

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='.')
```

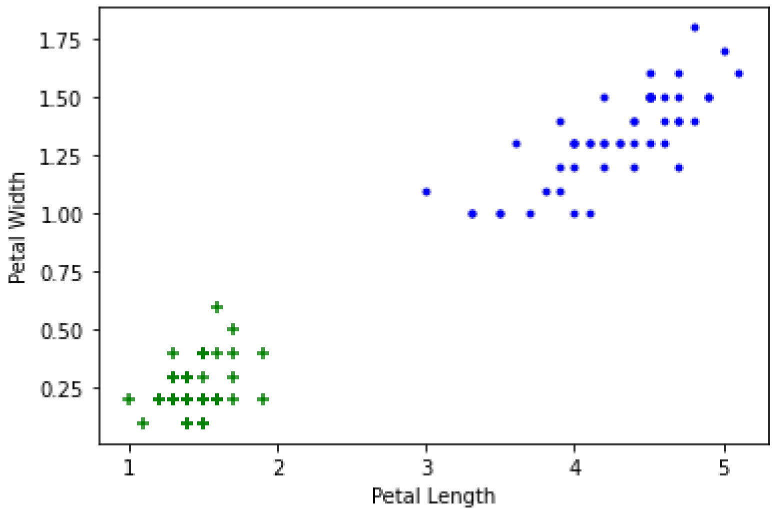
```
<matplotlib.collections.PathCollection at 0x7f14938e3a10>
```



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 0x7f14933d5b10>
```



Train Using Support Vector Machine (SVM)

```
from sklearn.model_selection import train_test_split
```

```
X = df.drop(['target','flower_name'], axis='columns')
y = df.target
```

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

```
len(X_train)
```

```
120
```

```
len(X_test)
```

```
30
```

```
from sklearn.svm import SVC
model = SVC()
```

```
model.fit(X_train, y_train)
```

```
SVC()
```

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

```
0.9666666666666667
```

```
model.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])
```

Tune parameters

1. Regularization (C)

The Regularization parameter (often termed as C parameter in python's sklearn library) tells the SVM optimization how much you want to avoid misclassifying each training example.

```
model_C = SVC(C=1)
model_C.fit(X_train, y_train)
model_C.score(X_test, y_test)
```

```
0.9666666666666667
```

```
model_C = SVC(C=10)
model_C.fit(X_train, y_train)
model_C.score(X_test, y_test)
```

```
0.9666666666666667
```

2. Gamma

Gamma parameter: gamma determines the distance a single data sample exerts influence. That is, the gamma parameter can be said to adjust the curvature of the decision boundary.

```
model_g = SVC(gamma=10)
model_g.fit(X_train, y_train)
model_g.score(X_test, y_test)
```

```
0.9666666666666667
```

3. Kernel

A kernel is a specialized kind of similarity function. It takes two points as input, and returns their similarity as output, just as a similarity metric does. A mathematical result from linear algebra known as Mercer's theorem has the implication that a broad class of functions (e.g. similarity metrics) may be expressed in terms of a dot product in some (possibly very and even infinitely) high dimensional space. This means that calculations performed on points in high-dimensional spaces may be restated in terms of dot products

```
model_linear_kernal = SVC(kernel='linear')
model_linear_kernal.fit(X_train, y_train)
```

```
SVC(kernel='linear')
```

```
model_linear_kernal.score(X_test, y_test)
```

```
0.9666666666666667
```

Exercise

Train SVM classifier using sklearn digits dataset (i.e. from sklearn.datasets import load_digits) and then,

1. Measure accuracy of your model using different kernels such as rbf and linear.
2. Tune your model further using regularization and gamma parameters and try to come up with highest accurancy score
3. Use 80% of samples as training data size

```
import pandas as pd

import numpy as np

import sklearn

import matplotlib.pyplot as plt
```

```
from sklearn.datasets import load_digits

import seaborn as sns


digits=load_digits()

print(digits)
```

```
{'data': array([[ 0.,  0.,  5., ...,  0.,  0.,  0.],
       [ 0.,  0.,  0., ..., 10.,  0.,  0.],
       [ 0.,  0.,  0., ..., 16.,  9.,  0.],
       ...,
       [ 0.,  0.,  1., ...,  6.,  0.,  0.],
       [ 0.,  0.,  2., ..., 12.,  0.,  0.],
       [ 0.,  0., 10., ..., 12.,  1.,  0.]]), 'target': array([0, 1, 2, ..., 8, 9, 8]
        [ 0.,  0., 13., ..., 15.,  5.,  0.],
        [ 0.,  3., 15., ..., 11.,  8.,  0.],
        ...,
        [ 0.,  4., 11., ..., 12.,  7.,  0.],
        [ 0.,  2., 14., ..., 12.,  0.,  0.],
        [ 0.,  0.,  6., ...,  0.,  0.,  0.]],

       [[ 0.,  0.,  0., ...,  5.,  0.,  0.],
        [ 0.,  0.,  0., ...,  9.,  0.,  0.],
        [ 0.,  0.,  3., ...,  6.,  0.,  0.],
        ...,
        [ 0.,  0.,  1., ...,  6.,  0.,  0.],
        [ 0.,  0.,  1., ...,  6.,  0.,  0.],
        [ 0.,  0.,  0., ..., 10.,  0.,  0.]],

       [[ 0.,  0.,  0., ..., 12.,  0.,  0.],
        [ 0.,  0.,  3., ..., 14.,  0.,  0.],
        [ 0.,  0.,  8., ..., 16.,  0.,  0.],
        ...,
        [ 0.,  9., 16., ...,  0.,  0.,  0.],
        [ 0.,  3., 13., ..., 11.,  5.,  0.],
        [ 0.,  0.,  0., ..., 16.,  9.,  0.]],

       ...,

       [[ 0.,  0.,  1., ...,  1.,  0.,  0.],
        [ 0.,  0., 13., ...,  2.,  1.,  0.],
        [ 0.,  0., 16., ..., 16.,  5.,  0.],
        ...,
        [ 0.,  0., 16., ..., 15.,  0.,  0.],
        [ 0.,  0., 15., ..., 16.,  0.,  0.],
        [ 0.,  0.,  2., ...,  6.,  0.,  0.]],

       [[ 0.,  0.,  2., ...,  0.,  0.,  0.],
        [ 0.,  0., 14., ..., 15.,  1.,  0.],
        [ 0.,  4., 16., ..., 16.,  7.,  0.],
        ...,
        [ 0.,  0.,  0., ..., 16.,  2.,  0.],
        [ 0.,  0.,  4., ..., 16.,  2.,  0.],
        [ 0.,  0.,  5., ..., 12.,  0.,  0.]],

       [[ 0.,  0., 10., ...,  1.,  0.,  0.],
```

```
        [ 0.,  2., 16., ...,  1.,  0.,  0.],
        [ 0.,  0., 15., ..., 15.,  0.,  0.],
        ...,
        [ 0.,  4., 16., ..., 16.,  6.,  0.],
        [ 0.,  8., 16., ..., 16.,  8.,  0.],
        [ 0.,  1.,  8., ..., 12.,  1.,  0.]]]), 'DESCR': ".. _digits_dataset:\n\nOpti
```

```
digits.keys()
```

```
dict_keys(['data', 'target', 'frame', 'feature_names', 'target_names', 'images', 'DES
```

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

print(df.head())

print(df.shape)
```

```
     0    1    2     3     4     5    6    7    8    9  ...   54   55   56  \
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
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
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
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
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

    57   58    59    60    61   62   63
0  0.0  6.0  13.0  10.0   0.0  0.0  0.0
1  0.0  0.0  11.0  16.0  10.0  0.0  0.0
2  0.0  0.0   3.0  11.0  16.0  9.0  0.0
3  0.0  7.0  13.0  13.0   9.0  0.0  0.0
4  0.0  0.0   2.0  16.0   4.0  0.0  0.0

[5 rows x 64 columns]
(1797, 64)
```

```
df.columns
```

```
RangeIndex(start=0, stop=64, step=1)
```

```
df.isnull().sum()
```

```
0     0
1     0
2     0
3     0
4     0
     ..
59    0
60    0
61    0
62    0
63    0
Length: 64, dtype: int64
```

```
df['target']=digits.target
```

```
df.head()
```

	0	1	2	3	4	5	6	7	8	9	...	55	56	57	58	59	60
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	10.0
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	16.0
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	11.0
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	13.0
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	16.0

5 rows × 65 columns

```
print(digits.data.shape)
```

```
print(digits.target.shape)
```

```
(1797, 64)
(1797,)
```

```
df.target
```

```
0       0
1       1
2       2
3       3
4       4
       ..
1792    9
1793    0
1794    8
1795    9
1796    8
Name: target, Length: 1797, dtype: int64
```

```
df.values
```

```
array([[ 0.,  0.,  5., ...,  0.,  0.,  0.],
       [ 0.,  0.,  0., ...,  0.,  0.,  1.],
       [ 0.,  0.,  0., ...,  9.,  0.,  2.],
       ...,
       [ 0.,  0.,  1., ...,  0.,  0.,  8.],
       [ 0.,  0.,  2., ...,  0.,  0.,  9.],
       [ 0.,  0., 10., ...,  1.,  0.,  8.]])
```

```
from sklearn.model_selection import train_test_split
```

```
x=df.drop(['target'],axis='columns')
```

```
y=df.target

x_train,x_test,y_train,y_test= train_test_split(x,y,test_size=0.2,random_state=12)



print(len(x_train))

print(len(x_test))
```

```
1437
360
```

```
from sklearn.metrics import accuracy_score

from sklearn.svm import SVC

model1=SVC(kernel='rbf',random_state=0, probability=True)

model1.fit(x_train,y_train)

y_pred_1=model1.predict(x_test)

print("Model Score of Kernal(rbf) :", model1.score(x_test,y_test))
```

```
Model Score of Kernal(rbf) : 0.9916666666666667
```

```
model2=SVC(kernel='linear',random_state=0, probability=True)

model2.fit(x_train,y_train)

y_pred_2=model2.predict(x_test)

print("Model Score of Kernal(linear) :", model2.score(x_test,y_test))
```

```
Model Score of Kernal(linear) : 0.975
```

```
model3=SVC(kernel='poly',random_state=0, probability=True)

model3.fit(x_train,y_train)

y_pred_3=model3.predict(x_test)

print("Model Score of Kernal(poly) :", model3.score(x_test,y_test))
```

```
Model Score of Kernal(poly) : 0.9944444444444445
```

```
accuracy=accuracy_score(y_test,y_pred_3)
```

```
print('ACCURACY is',accuracy)
```

```
ACCURACY is 0.9944444444444445
```

```
from sklearn.metrics import confusion_matrix
```

```
cm=np.array(confusion_matrix(y_test,y_pred_3))
```

```
cm
```

```
array([[37,  0,  0,  0,  0,  0,  0,  0,  0,  0],
       [ 0, 32,  0,  0,  0,  0,  0,  0,  0,  0],
       [ 0,  0, 38,  0,  0,  0,  0,  0,  0,  0],
       [ 0,  0,  0, 43,  0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0, 39,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  0, 32,  0,  0,  0,  2],
       [ 0,  0,  0,  0,  0,  0, 29,  0,  0,  0],
       [ 0,  0,  0,  0,  0,  0,  0, 42,  0,  0],
       [ 0,  0,  0,  0,  0,  0,  0,  0, 32,  0],
       [ 0,  0,  0,  0,  0,  0,  0,  0,  0, 34]])
```

```
from sklearn.metrics import mean_squared_error
```

```
mse=mean_squared_error(y_test,y_pred_3)
```

```
mse
```

```
0.08888888888888889
```

```
model1_C=SVC(C=3)
```

```
model1_C.fit(x_train,y_train)
```

```
model1_C.score(x_test,y_test)
```

```
0.9944444444444445
```

```
model2_C=SVC(C=3)
```

```
model2_C.fit(x_train,y_train)
```

```
model2_C.score(x_test,y_test)
```

```
0.9944444444444445
```

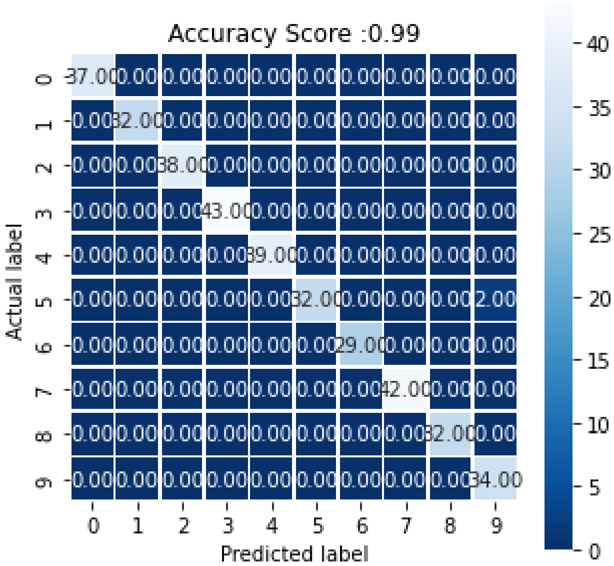
```
model3_C=SVC(C=3)
```

```
model3_C.fit(x_train,y_train)
```

```
model3_C.score(x_test,y_test)
```

```
0.9944444444444445
```

```
plt.figure(figsize=(5,5))

sns.heatmap(cm, annot=True, fmt=".2f", linewidths=.5, square = True, cmap = 'Blues_r')

plt.ylabel('Actual label')

plt.xlabel('Predicted label')

A=f'Accuracy Score :{accuracy:.2f}'

plt.title(A)

plt.show()
```



1s completed at 1:54 PM

Name : Kshitij V Darwhekar

Roll No: TETB19

Sub: Soft Computitng

Batch: B2

Experiment 5 : To implement both the k-means algorithm and the Hierarchical Agglomerative Clustering (HAC) algorithm

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

```
from google.colab import drive
drive.mount('/content/drive')
df1 = pd.read_csv('/content/drive/MyDrive/ML/shopping-data.csv')
```

```
Mounted at /content/drive
```

Implementation of hierarchial clustering

```
df1.shape
```

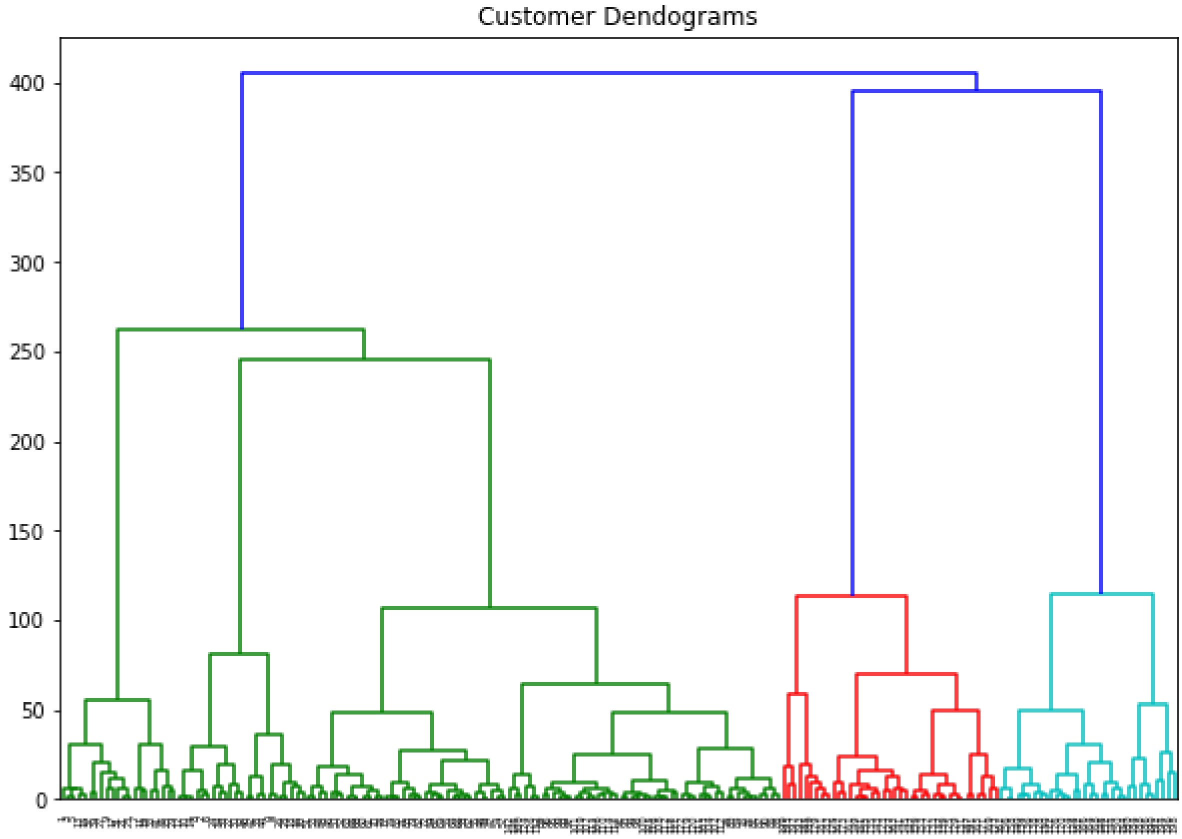
```
(200, 5)
```

```
df1.head()
```

	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

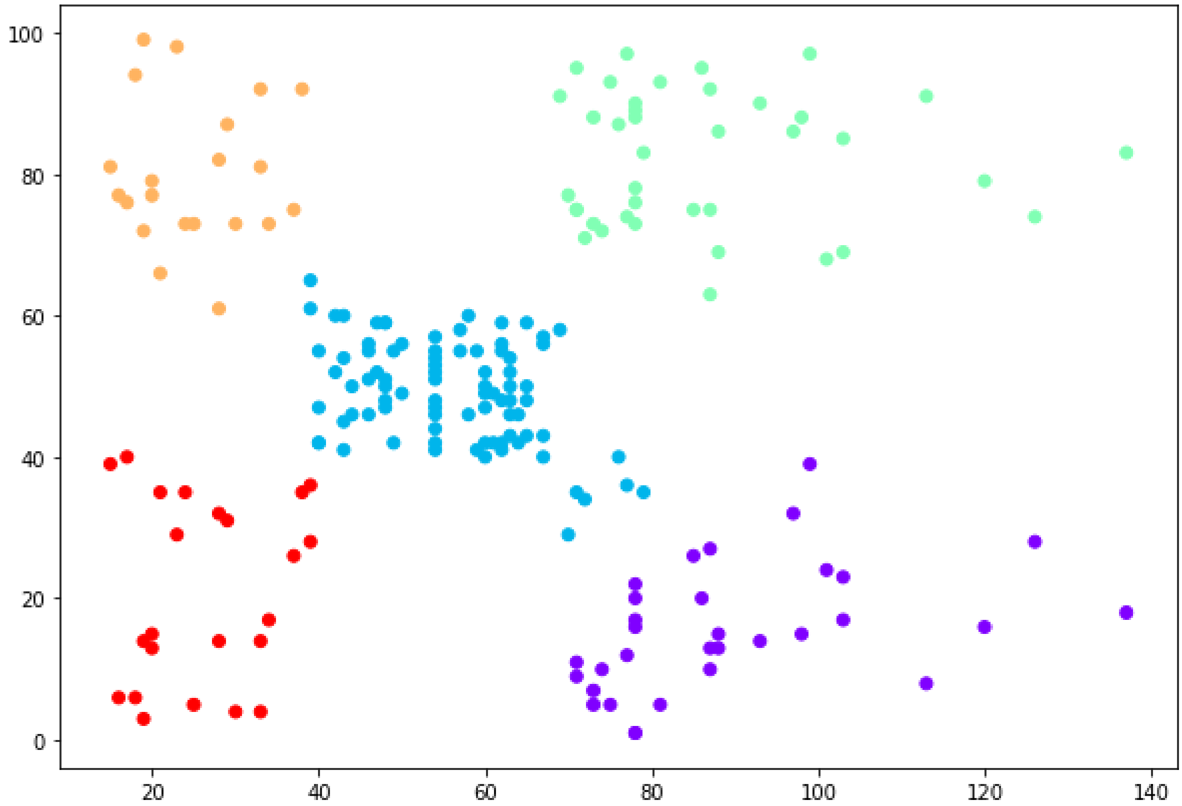
```
data = df1.iloc[:, 3:5].values
```

```
import scipy.cluster.hierarchy as shc

plt.figure(figsize=(10, 7))
plt.title("Customer Dendograms")
dend = shc.dendrogram(shc.linkage(data, method='ward'))
```




```
from sklearn.cluster import AgglomerativeClustering

cluster = AgglomerativeClustering(n_clusters=5, affinity='euclidean', linkage='ward')
cluster.fit_predict(data)

    array([4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3,
           4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 1,
           4, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
           1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
           1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
           1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 2, 1, 2, 0, 2, 0, 2,
           1, 2, 0, 2, 0, 2, 0, 2, 0, 2, 1, 2, 0, 2, 1, 2, 0, 2, 0, 2, 0, 2,
           0, 2, 0, 2, 0, 2, 1, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
           0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
           0, 2])


plt.figure(figsize=(10, 7))
plt.scatter(data[:,0], data[:,1], c=cluster.labels_, cmap='rainbow')
```

<matplotlib.collections.PathCollection at 0x7f658ce67f90>



Name : Kshitij V Darwhekar

Roll No: TETB19

Sub: Soft Computitng

Batch: B2

Experiment 6: Implementation of IOT Solution using Machine Learning

Importing the libraries

```
import sklearn
import numpy as np
import pandas as pd
```

Importing the dataset

```
from google.colab import drive
drive.mount('/content/drive/')
```

```
Drive already mounted at /content/drive/; to attempt to forcibly remount, call drive
```

```
dataset = pd.read_csv("/content/drive/MyDrive/ML/Crop_recommendation.csv")
```

```
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values
```

```
dataset.head()
```

N	P	K	temperature	humidity	ph	rainfall	label

Data Preprocessing

2 60 55 44 23.004459 82.320763 7.840207 263.964248 rice

Taking care of missing data

```
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(missing_values=np.nan, strategy='mean')
imputer.fit(X[:,:])
X[:, :] = imputer.transform(X[:, :])
```

Encoding categorical data

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
y = le.fit_transform(y)
```

Splitting the dataset into the Training set and Test set

```
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 =
```

```
print(X_train)
```

```
[[134.          56.          18.         ...  83.91902605   6.6912681
   70.97358303]
 [ 29.         122.         196.         ...  81.15595212   5.63832848
   73.06862952]
 [ 25.          68.          19.         ...  64.25510719   7.10845012
   67.47677295]
 ...
 [ 35.          64.          15.         ...  63.53604453   6.50014496
   69.5274407 ]
 [ 39.          65.          23.         ...  69.12613376   7.6859593
   41.02682925]
 [ 14.          22.           9.         ...  91.13772765   6.54319181
  112.5090516 ]]
```

```
print(y_train)
```

```
[ 6  7  2 ...  2 10 16]
```

```
print(X_test)
```

```
[[105.          14.          50.         ...  87.6883982    6.41905219
   59.65590798]
 [ 91.          12.          46.         ...  85.49938185   6.34394252
   48.31219031]
 [ 14.         121.         203.         ...  83.74765639   6.15868941
   74.46411148]
 ...
 [ 84.          27.          29.         ...  53.00366334   7.16709259
  168.2644287 ]
 [ 31.          13.          33.         ...  95.21224392   6.34246371
  148.3003692 ]
 [  5.          24.          40.         ...  93.87030088   6.29790758
  104.6735454 ]]
```

```
print(y_test)
```

```
[21 21  7  3  2 20 13  9 15  1 13  5 10 14 12  0  5 10  5 12  4  2  9  8
  6  5 10 16 13  9 19 20 11 15  4  6 12 12 21 13 11  2 18 21 18 14  9  9
  6 14 13  2  0 15 18  1 17 12 10  6 16 14 21 20 15  0  7  5  0 16  4 19
  9 11  7 13  3 11  8 12 20  2 21 21 15  6 11 10 13 17  2  8 14  7 14 11
  5  8 10  3 16  8 14  1  1 20 21  5 18 15 15 12  5  7 16 19 14 10 11  8
 19 10 16  3  3  2 19 16  3 17 13 13 15 14 11 14  4 19 16  2  2  7  0  5
  3  0  8 12 21 17 16  4 13  1 19  3 21  2  0  8 10 18  8  9  9 15 20 15
  1 16 18  0 13  4  6 14  9 19 17 16 20 17 17 18  9  1  4 18 20 17 11  8
 13 20 11  5 18  4  3 12  4 19 11 13 13 16 15 11 18  1  3  2 18 16 13 14
 12 17 15 19 20 20  2 17  2  5 11  5 16 20 13 14 16  9 19  4 12 14  6 20
  3 14  0 18  2 20 21  2 19 16 11  7  3 18  8 17 19  5 12 13  8 21 19 20
  7  4  8 10  3  5  5 17 19 11 20  3 18 16 19 18  4  9 19 15 13 12 10  1
  2 12  9 12  6 14 17  7  7 18 17  8 20  3 15  5 21 20  8 17  7 15  2 13
 13  3  2 12  1 12 19  8 16 15  3 10  6 17  7  9 10  0 20 15  0 17  2  8
  3 13 10  7  8  9 15 17  7 17 20  5 15 13  1 17 16  9 21 18  0 21 21 18
  9 13  9  8  4  6  9 16  6 18 19  6  6  0  6  0 16 11  7  1  0 13 20  9
  1 20 10  3 19  1  3 15 19  0 10 15 16  2 15 13 12  3 19 12  3  4 15  1
 18 17  8 10  6 20  1  4 20  2 11 16 21 20  0  7 18  7  3 12  8 19 11 12
  7  1 14 18  1  6  2  0  0  8  8 21  3  1 19  1  9  7 11  5 11  8  7  5
 14  2  8 16 18 18 15 13 21 14 21 17 14 14 14 19 16 13  0  5  4 11  4  7
  7  3  3 12  9 17 16 14 17 18  2 17 15  2  1 20  5  6  7  8  3 15  1  7
 21 15 18  8 18  6 21 19  5  4 11 20 14  9 21 14  0  0 21  1 13 14  0 14
  6 20 17  6 17  3  0 19 13 20  2 12 16  8  1 17  5  6 12  5  4 19]
```

Feature Scaling

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

```
print(X_train)
```

```
[[ 2.25367108  0.07555744 -0.59141091 ...  0.56115786  0.28639844
  -0.58838147]
 [-0.58434455  2.06834149  2.90385791 ...  0.43651791 -1.09903674
  -0.55053196]
```

```
 [-0.69245943  0.43788181 -0.57177457 ... -0.3258651   0.83531751
  -0.65155552]
 ...
 [-0.42217223  0.31710702 -0.65031993 ... -0.35830141  0.03492274
  -0.61450776]
 [-0.31405735  0.34730072 -0.4932292  ... -0.10613716  1.5951916
  -1.12940532]
 [-0.98977536 -0.95102828 -0.76813798 ...  0.88678747  0.09156286
   0.16200634]]
```

```
print(X_test)
```

```
[[ 1.46983819 -1.19257786  0.03695202 ...  0.73119109 -0.07177737
  -0.79284878]
 [ 1.09143611 -1.25296526 -0.04159334 ...  0.63244639 -0.17060505
  -0.99778658]
 [-0.98977536  2.03814779  3.0413123  ...  0.55342752 -0.41435709
  -0.52532091]
 ...
 [ 0.90223507 -0.80005979 -0.37541115 ... -0.83340833  0.91247799
   1.16929376]
 [-0.53028711 -1.22277156 -0.29686578 ...  1.07058549 -0.17255083
   0.8086192 ]
 [-1.23303384 -0.89064089 -0.15941139 ...  1.01005156 -0.23117683
   0.02044856]]
```

Random Forest

Training the Random Forest Classification model on the Training set

```
from sklearn.ensemble import RandomForestClassifier
classifier = RandomForestClassifier(n_estimators = 10, criterion = 'entropy', random_state
classifier.fit(X_train, y_train)
```

```
RandomForestClassifier(criterion='entropy', n_estimators=10, random_state=0)
```

Predicting the Test set results

```
y_pred_RF = classifier.predict(X_test)
print(np.concatenate((y_pred_RF.reshape(len(y_pred_RF),1), y_test.reshape(len(y_test),1)),
```

```
[[21 21]
 [21 21]
 [ 7  7]
 ...
 [ 5  5]
```

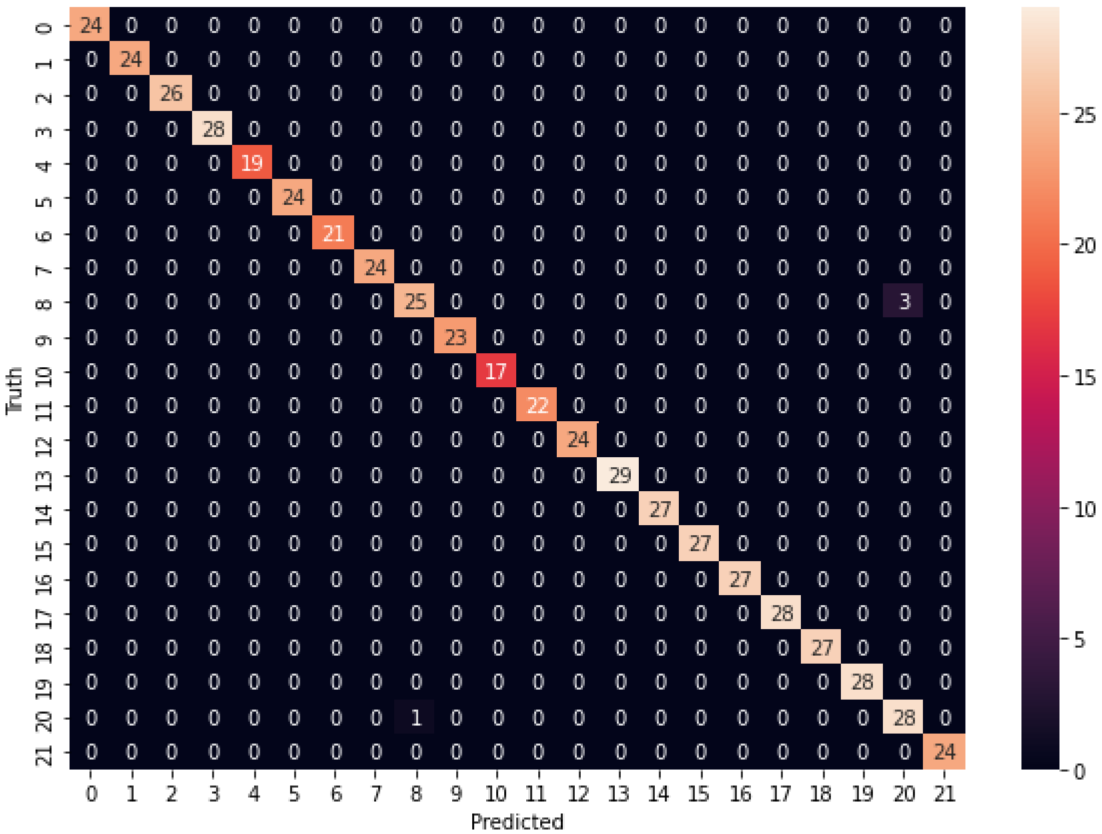
```
 [ 4  4]
 [19 19]]
```

Making the Confusion Matrix

```
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred_RF)
```

```
%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')
```

```
Text(69.0, 0.5, 'Truth')
```



```
accuracy_score(y_test, y_pred_RF)
```

```
0.9927272727272727
```

Naive Bayes

Training the Naive Bayes model on the Training set

```
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(X_train, y_train)
```

```
    GaussianNB()
```

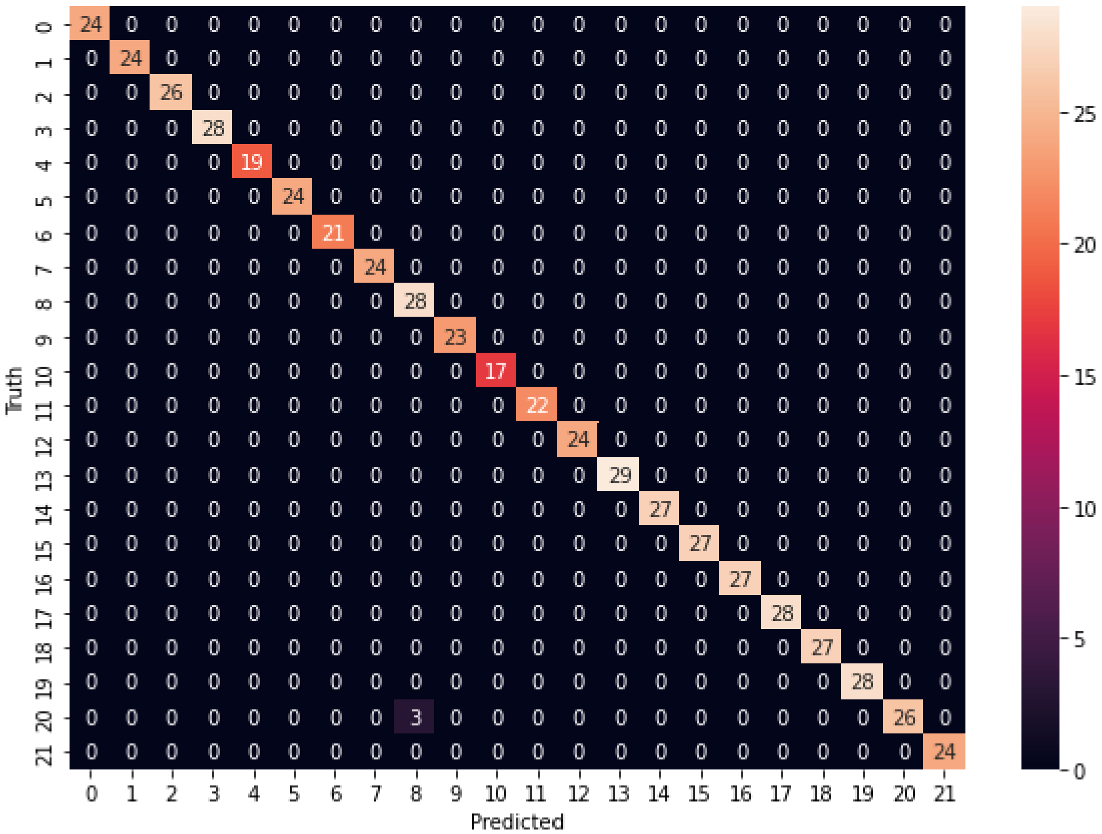
```
y_pred_NV = classifier.predict(X_test)
print(np.concatenate((y_pred_NV.reshape(len(y_pred_NV),1), y_test.reshape(len(y_test),1)),
```

```
    [[21 21]
     [21 21]
     [ 7  7]
     ...
     [ 5  5]
     [ 4  4]
     [19 19]]
```

```
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred_NV)
```

```
%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')
```

```
    Text(69.0, 0.5, 'Truth')
```



```
accuracy_score(y_test, y_pred_NV)
```

```
0.9945454545454545
```

Name : Kshitij V Darwhekar

Roll No: TETB19

Sub: Soft Computitng

Batch: B2

```
import tensorflow
```

```
from tensorflow import keras
```

```
import tensorflow as tf
from tensorflow import keras
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
```

```
(X_train, y_train) , (X_test, y_test) = keras.datasets.mnist.load_data()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mni
11493376/11490434 [==============================] - 0s 0us/step
11501568/11490434 [==============================] - 0s 0us/step
```

```
len(X_train)
```

```
60000
```

```
len(X_test)
```

To undo cell deletion use Ctrl+M Z or the Undo option in the Edit menu

```
X_train[0].shape
```

```
(28, 28)
```

```
X_train[0]
```

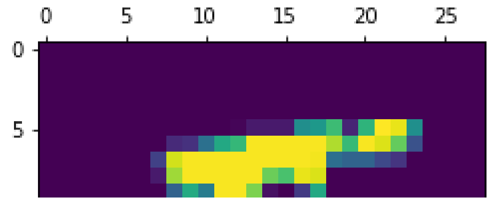
```
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,  80, 156, 107, 253, 253,
        205,  11,   0,  43, 154,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,  14,   1, 154, 253,
         90,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0, 139, 253,
        190,   2,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  11, 190,
        253,  70,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
```

```
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  35,
        241, 225, 160, 108,   1,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
         81, 240, 253, 253, 119,  25,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,  45, 186, 253, 253, 150,  27,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0,  16,  93, 252, 253, 187,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0,   0,   0, 249, 253, 249,  64,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,  46, 130, 183, 253, 253, 207,   2,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  39,
        148, 229, 253, 253, 253, 250, 182,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  24, 114, 221,
        253, 253, 253, 253, 201,  78,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,  23,  66, 213, 253, 253,
        253, 253, 198,  81,   2,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,  18, 171, 219, 253, 253, 253, 253,
        195,  80,   9,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,  55, 172, 226, 253, 253, 253, 253, 244, 133,
         11,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0, 136, 253, 253, 253, 212, 135, 132,  16,   0,
          0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
                                                       0,   0,   0,
                                                       0,   0,   0,
          0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0]], dtype=uint8)
```

To undo cell deletion use Ctrl+M Z or the Undo option in the Edit menu ×

```
plt.matshow(X_train[0])
```

```
<matplotlib.image.AxesImage at 0x7efc976e77d0>
```




```
y_train[0]
```

```
5
```

```
# Scaling Technique

X_train = X_train / 255
X_test = X_test / 255
```

```
X_train[0]
```

```
          0.        , 0.        , 0.        , 0.        , 0.18039216,
          0.50980392, 0.71764706, 0.99215686, 0.99215686, 0.81176471,
          0.00784314, 0.        , 0.        , 0.        , 0.        ,
          0.        , 0.        , 0.        ],
         [0.        , 0.        , 0.        , 0.        , 0.        ,
          0.        , 0.        , 0.        , 0.        , 0.        ,
          0.        , 0.        , 0.15294118, 0.58039216, 0.89803922,
          0.99215686, 0.99215686, 0.99215686, 0.98039216, 0.71372549,
          0.        , 0.        , 0.        , 0.        , 0.        ,
          0.        , 0.        , 0.        ],
         [0.        , 0.        , 0.        , 0.        , 0.        ,
          0.        , 0.        , 0.        , 0.        , 0.        ,
          0.09411765, 0.44705882, 0.86666667, 0.99215686, 0.99215686,
          0.99215686, 0.99215686, 0.78823529, 0.30588235, 0.        ,
          0.        , 0.        , 0.        , 0.        , 0.        ,
          0.        , 0.        , 0.        ],
         [0.        , 0.        , 0.        , 0.        , 0.        ,
                                                          25882353,
                                                          99215686,
          0.77647059, 0.31764706, 0.00784314, 0.        , 0.        ,
          0.        , 0.        , 0.        , 0.        , 0.        ,
          0.        , 0.        , 0.        ],
         [0.        , 0.        , 0.        , 0.        , 0.        ,
          0.        , 0.07058824, 0.67058824, 0.85882353, 0.99215686,
          0.99215686, 0.99215686, 0.99215686, 0.76470588, 0.31372549,
          0.03529412, 0.        , 0.        , 0.        , 0.        ,
          0.        , 0.        , 0.        , 0.        , 0.        ,
          0.        , 0.        , 0.        ],
         [0.        , 0.        , 0.        , 0.        , 0.21568627,
          0.6745098 , 0.88627451, 0.99215686, 0.99215686, 0.99215686,
          0.99215686, 0.95686275, 0.52156863, 0.04313725, 0.        ,
          0.        , 0.        , 0.        , 0.        , 0.        ,
          0.        , 0.        , 0.        , 0.        , 0.        ,
          0.        , 0.        , 0.        ],
         [0.        , 0.        , 0.        , 0.        , 0.53333333,
          0.99215686, 0.99215686, 0.99215686, 0.83137255, 0.52941176,
          0.51764706, 0.0627451 , 0.        , 0.        , 0.        ,
          0.        , 0.        , 0.        , 0.        , 0.        ,
          0.        , 0.        , 0.        , 0.        , 0.        ,
```

To undo cell deletion use Ctrl+M Z or the Undo option in the Edit menu

```
 0.        , 0.        , 0.        ],
[0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        ],
[0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        ],
[0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        ]])
```

```
X_train_flattened = X_train.reshape(len(X_train), 28*28)
X_test_flattened = X_test.reshape(len(X_test), 28*28)
```

```
X_train_flattened.shape
```

```
(60000, 784)
```

```
X_test_flattened.shape
```

```
(10000, 784)
```

```
X_train_flattened[0]
```

```
0.97647059, 0.25098039, 0.        , 0.        , 0.        ,
```

To undo cell deletion use Ctrl+M Z or the Undo option in the Edit menu

```
0.        , 0.        , 0.        , 0.18039216, 0.50980392,
0.71764706, 0.99215686, 0.99215686, 0.81176471, 0.00784314,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.15294118,
0.58039216, 0.89803922, 0.99215686, 0.99215686, 0.99215686,
0.98039216, 0.71372549, 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.09411765, 0.44705882, 0.86666667, 0.99215686, 0.99215686,
0.99215686, 0.99215686, 0.78823529, 0.30588235, 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.09019608, 0.25882353, 0.83529412, 0.99215686,
0.99215686, 0.99215686, 0.99215686, 0.77647059, 0.31764706,
0.00784314, 0.        , 0.        , 0.        , 0.        ,
```

```
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.07058824, 0.67058824, 0.85882353,
        0.99215686, 0.99215686, 0.99215686, 0.99215686, 0.76470588,
        0.31372549, 0.03529412, 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.21568627, 0.6745098 ,
        0.88627451, 0.99215686, 0.99215686, 0.99215686, 0.99215686,
        0.95686275, 0.52156863, 0.04313725, 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.53333333, 0.99215686, 0.99215686, 0.99215686,
        0.83137255, 0.52941176, 0.51764706, 0.0627451 , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        ])
```

```
# 10 Output neuron and 784 in input neuron
model = keras.Sequential([
```

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```
oid')
```

```
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.fit(X_train_flattened, y_train, epochs=5)
```

```
Epoch 1/5
1875/1875 [==============================] - 3s 1ms/step - loss: 0.4724 - accuracy: 0
Epoch 2/5
1875/1875 [==============================] - 3s 2ms/step - loss: 0.3034 - accuracy: 0
Epoch 3/5
1875/1875 [==============================] - 4s 2ms/step - loss: 0.2833 - accuracy: 0
Epoch 4/5
1875/1875 [==============================] - 5s 3ms/step - loss: 0.2731 - accuracy: 0
Epoch 5/5
1875/1875 [==============================] - 5s 3ms/step - loss: 0.2664 - accuracy: 0
<keras.callbacks.History at 0x7efc93077f50>
```

```
model.evaluate(X_test_flattened, y_test)
```

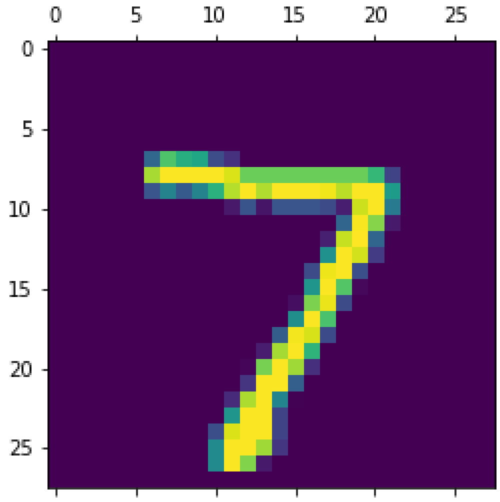
```
313/313 [==============================] - 1s 2ms/step - loss: 0.2695 - accuracy: 0.9
[0.2695145010948181, 0.9254000186920166]
```

```
y_predicted = model.predict(X_test_flattened)
y_predicted[0]
```

```
array([1.5027165e-02, 3.9325224e-07, 6.3410342e-02, 9.5975685e-01,
       3.2548308e-03, 1.0176152e-01, 1.0720740e-06, 9.9978119e-01,
       7.0441395e-02, 6.0749489e-01], dtype=float32)
```

```
plt.matshow(X_test[0])
```

```
<matplotlib.image.AxesImage at 0x7efc920031d0>
```




```
# np.argmax finds a maximum element from an array and returns the index of it
```

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```
7
```

```
y_predicted_labels = [np.argmax(i) for i in y_predicted]
```

```
y_predicted_labels[:5]
```

```
[7, 2, 1, 0, 4]
```

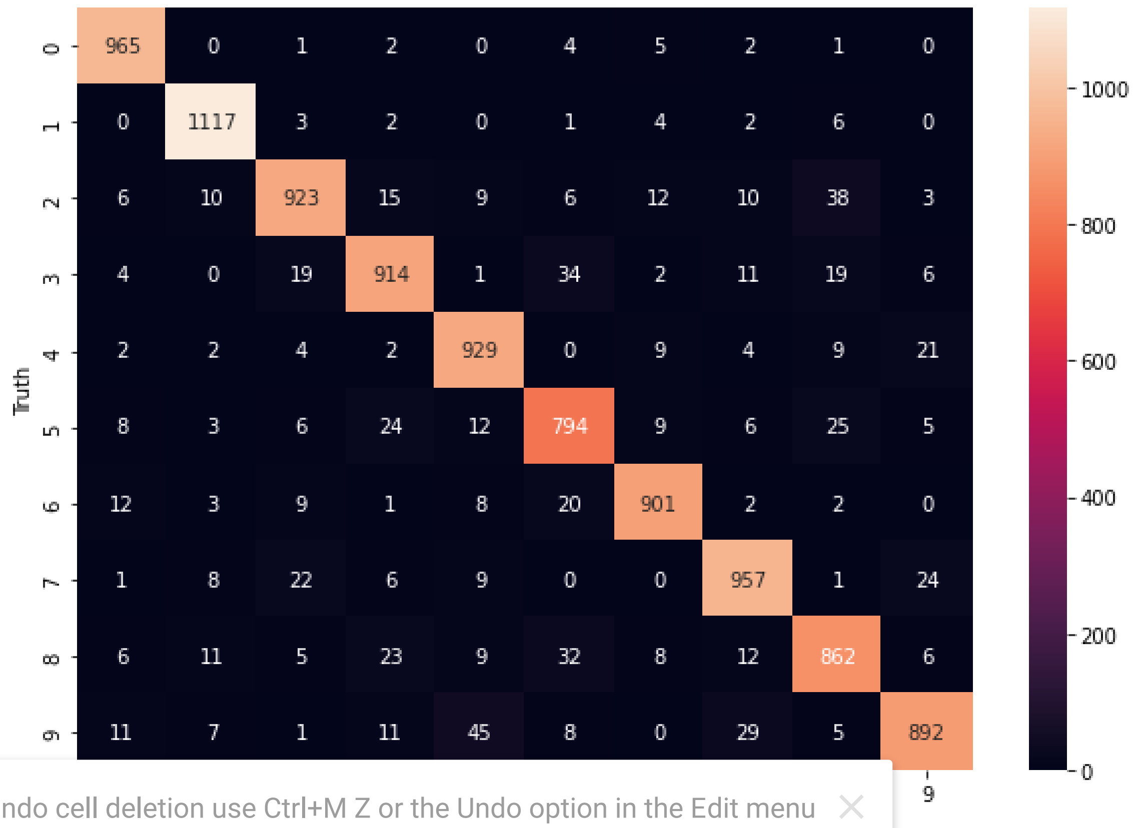
```
cm = tf.math.confusion_matrix(labels=y_test,predictions=y_predicted_labels)
cm
```

```
<tf.Tensor: shape=(10, 10), dtype=int32, numpy=
array([[ 965,    0,    1,    2,    0,    4,    5,    2,    1,    0],
       [   0, 1117,    3,    2,    0,    1,    4,    2,    6,    0],
       [   6,   10,  923,   15,    9,    6,   12,   10,   38,    3],
       [   4,    0,   19,  914,    1,   34,    2,   11,   19,    6],
```

```
       [   2,    2,    4,    2,  929,    0,    9,    4,    9,   21],
       [   8,    3,    6,   24,   12,  794,    9,    6,   25,    5],
       [  12,    3,    9,    1,    8,   20,  901,    2,    2,    0],
       [   1,    8,   22,    6,    9,    0,    0,  957,    1,   24],
       [   6,   11,    5,   23,    9,   32,    8,   12,  862,    6],
       [  11,    7,    1,   11,   45,    8,    0,   29,    5,  892]],
      dtype=int32)>
```

```
import seaborn as sn
plt.figure(figsize = (10,7))
sn.heatmap(cm, annot=True, fmt='d')
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

```
    Text(69.0, 0.5, 'Truth')
```



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Using hidden layer

```
model = keras.Sequential([
    keras.layers.Dense(100, input_shape=(784,), activation='relu'),
    keras.layers.Dense(10, activation='sigmoid')
])

model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.fit(X_train_flattened, y_train, epochs=5)
```

```
    Epoch 1/5
    1875/1875 [==============================] - 3s 2ms/step - loss: 0.2726 - accuracy: 0
```

```
Epoch 2/5
1875/1875 [==============================] - 3s 2ms/step - loss: 0.1230 - accuracy: 0
Epoch 3/5
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0852 - accuracy: 0
Epoch 4/5
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0660 - accuracy: 0
Epoch 5/5
1875/1875 [==============================] - 3s 1ms/step - loss: 0.0521 - accuracy: 0
<keras.callbacks.History at 0x7efc8ed501d0>
```

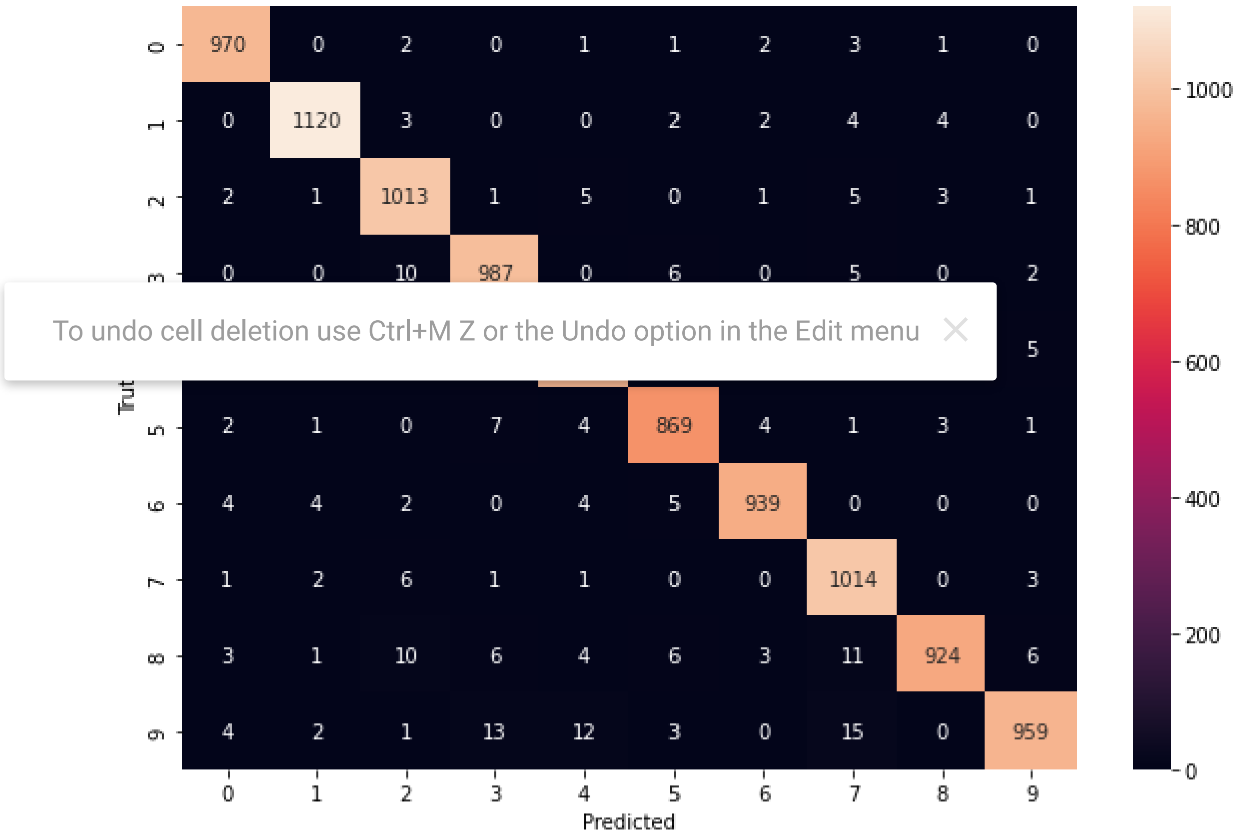
```
model.evaluate(X_test_flattened,y_test)
```

```
313/313 [==============================] - 0s 1ms/step - loss: 0.0786 - accuracy: 0.9
[0.07863084971904755, 0.9763000011444092]
```

```
y_predicted = model.predict(X_test_flattened)
y_predicted_labels = [np.argmax(i) for i in y_predicted]
cm = tf.math.confusion_matrix(labels=y_test,predictions=y_predicted_labels)

plt.figure(figsize = (10,7))
sn.heatmap(cm, annot=True, fmt='d')
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

```
Text(69.0, 0.5, 'Truth')
```



Using Flatten layer so that we don't have to call .reshape on input dataset

```
model = keras.Sequential([
    keras.layers.Flatten(input_shape=(28, 28)),
    keras.layers.Dense(100, activation='relu'),
    keras.layers.Dense(10, activation='sigmoid')
])

model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.fit(X_train, y_train, epochs=10)
```

```
Epoch 1/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.2693 - accuracy: 0
Epoch 2/10
1875/1875 [==============================] - 3s 1ms/step - loss: 0.1207 - accuracy: 0
Epoch 3/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0839 - accuracy: 0
Epoch 4/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0657 - accuracy: 0
Epoch 5/10
1875/1875 [==============================] - 6s 3ms/step - loss: 0.0490 - accuracy: 0
Epoch 6/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0408 - accuracy: 0
Epoch 7/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0332 - accuracy: 0
Epoch 8/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0281 - accuracy: 0
Epoch 9/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0225 - accuracy: 0
Epoch 10/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0196 - accuracy: 0
<keras.callbacks.History at 0x7efc92f47c90>
```

To undo cell deletion use Ctrl+M Z or the Undo option in the Edit menu

```
313/313 [==============================] - 0s 1ms/step - loss: 0.0913 - accuracy: 0.9
[0.0912703275680542, 0.9740999937057495]
```

✓ 0s completed at 4:17 PM

To undo cell deletion use Ctrl+M Z or the Undo option in the Edit menu

Name : Kshitij V Darwhekar

Roll No: TETB19

Sub: Soft Computitng

Batch: B2

Experiment 8 : Open CV for Computer Vision

In [ ]:

```
import cv2
```

In [ ]:

```
scale_percent = 20 # percent of original size
width = int(img.shape[1] * scale_percent / 100)
height = int(img.shape[0] * scale_percent / 100)
dim = (width,height)
```

In [ ]:

```
faceHar = cv2.CascadeClassifier('haarcascade_frontalface_default.xml')

img = cv2.imread('./Kshit.JPG')

imgGray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

faces = faceHar.detectMultiScale(imgGray, 1.1, 4)
```

In [ ]:

```
for (x, y ,w, h) in faces:
    cv2.rectangle(img, (x, y), (x+h, y+w), (0, 255, 0), 2)

resized = cv2.resize(img, dim, interpolation = cv2.INTER_AREA)
```

In [ ]:

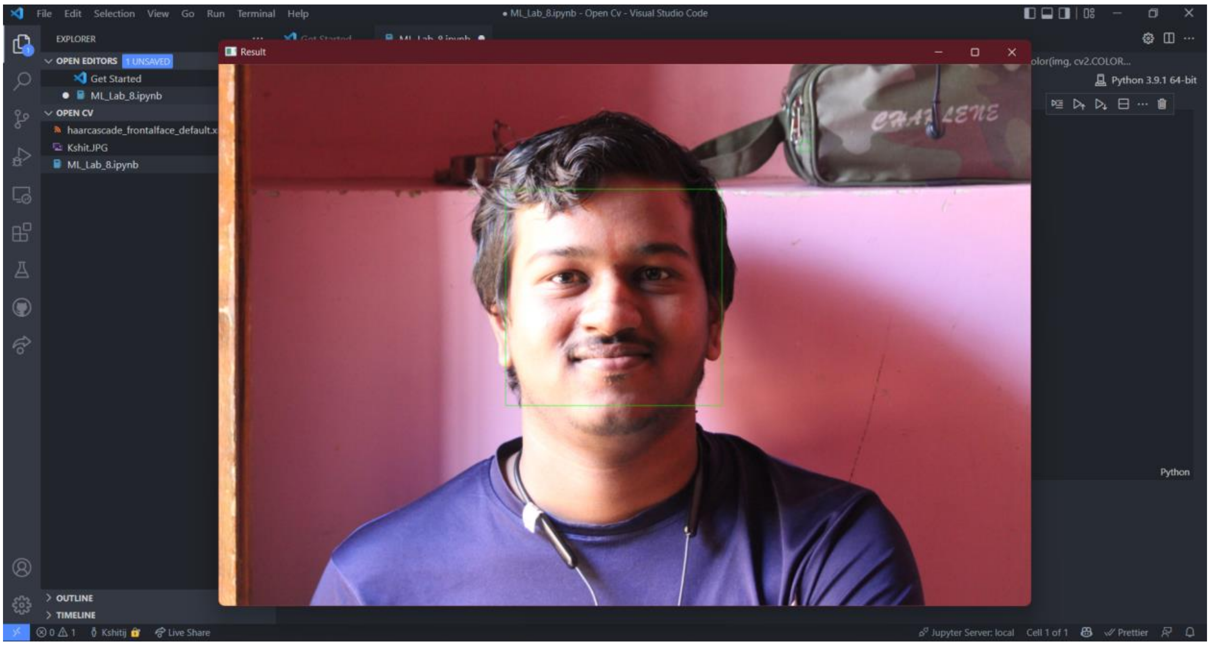
```
cv2.imshow("Result", resized)

cv2.waitKey(0)
```

Out[ ]:

```
-1
```

Output :


File Edit Selection View Go Run Terminal Help
● ML_Lab_8.ipynb - Open Cv - Visual Studio Code
EXPLORER
OPEN EDITORS 1 UNSAVED
Get Started
ML_Lab_8.ipynb
OPEN CV
haarcascade_frontalface_default.x
Kshit.JPG
ML_Lab_8.ipynb
Result
olor(img, cv2.COLOR...
Python 3.9.1 64-bit
Python
OUTLINE
TIMELINE
Kshitij
Live Share
Jupyter Server: local
Cell 1 of 1
Prettier