VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
ON
MACHINE LEARNING

Submitted by

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1BM21CS096

in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING

B.M.S. COLLEGE OF ENGINEERING
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B. M. S. College of Engineering,
Bull Temple Road, Bangalore 560019
(Affiliated To Visvesvaraya Technological University, Belgaum)

Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the Lab work entitled **"MACHINE LEARNING"** carried out by **Likhith G S(1BM21CS096)**, who is bonafide student of **B. M. S. College of Engineering**. It is in partial fulfillment for the award of **Bachelor of Engineering in Computer Science and Engineering** of the Visvesvaraya Technological University, Belgaum during the year 2023-24. The Lab report has been approved as it satisfies the academic requirements in respect of Machine Learning Lab - **(22CS6PCMAL)**work prescribed for the said degree.

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Index

Sl. No.	Experiment Title
1	Write a python program to import and export data using Pandas library functions
2	Demonstrate various data pre-processing techniques for a given dataset
3	Use an appropriate data set for building the decision tree (ID3) and apply this knowledge to classify a new sample.
4	Build KNN Classification model for a given dataset.
5	Implement Linear and Multi-Linear Regression algorithm using appropriate dataset
6	Build Logistic Regression Model for a given dataset
7	Build Support vector machine model for a given dataset
8	Build k-Means algorithm to cluster a set of data stored in a .CSV file.
9	Implement Dimensionality reduction using Principle Component Analysis (PCA) method.
10	Build Artificial Neural Network model with back propagation on a given dataset
11	a) Implement Random forest ensemble method on a given dataset. b) Implement Boosting ensemble method on a given dataset.

Course outcomes:

CO1	Apply machine learning techniques in computing systems
CO2	Evaluate the model using metrics
CO3	Design a model using machine learning to solve a problem
CO4	Conduct experiments to solve real-world problems using appropriate machine learning techniques

PROGRAM 1

Date:05-04-2024

Write a python program to import and export data using Pandas library functions

Date __/__/__
Page ______

5/4/24

Week - 1

① Reading from Downloaded CSV file

```
import pandas as pd.

df = pd.read_csv('austin Housing Data.csv')

df.head()
```

② Reading from URL

```
url = '..iris/iris.data'

col_names = ['sepal_length', 'sepal_width', 'class']

iris_data = pd.read_csv(url, names = col_names)

iris_data.head()
```

③ Exporting File .

```
iris_data.to_csv('cleaned_iris_data.csv')
```

Code Screenshot

```
[5]  import pandas as pd
```

```
[7]  data = pd.read_csv('/content/austinHousingData.csv')
```

```
[8]  data.head()
```

```
[9]  url = "https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data"

     col_names = ["sepal_length_in_cm",
                  "sepal_width_in_cm",
                  "petal_length_in_cm",
                  "petal_width_in_cm",
                  "class"]
     iris_data = pd.read_csv(url, names=col_names)
```

```
iris_data.head()
```

```
iris_data.to_csv("exported.csv")
```

Output:

	zpid	city	streetAddress	zipcode	description	latitude	longitude	propertyTaxRate	garageSpaces	hasAssociation	...	numOfMiddleSchools	numOfHighSchools	avgSchoolD
0	111373431	pflugerville	14424 Lake Victor Dr	78660	14424 Lake Victor Dr, Pflugerville, TX 78660 i...	30.430632	-97.663078	1.98	2	True	...	1	1	
1	120900430	pflugerville	1104 Strickling Dr	78660	Absolutely GORGEOUS 4 Bedroom home with 2 full...	30.432673	-97.661697	1.98	2	True	...	1	1	
2	2084491383	pflugerville	1408 Fort Dessau Rd	78660	Under construction - estimated completion in A...	30.409748	-97.639771	1.98	0	True	...	1	1	
3	120901374	pflugerville	1025 Strickling Dr	78660	Absolutely darling one story home in charming ...	30.432112	-97.661659	1.98	2	True	...	1	1	
4	60134862	pflugerville	15005 Donna Jane Loop	78660	Brimming with appeal & warm livability! Sleek ...	30.437368	-97.656860	1.98	0	True	...	1	1	

5 rows × 47 columns

exported.csv X

1 to 10 of 150 entries Filter

	sepal_length_in_cm	sepal_width_in_cm	petal_length_in_cm	petal_width_in_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
5	5.4	3.9	1.7	0.4
6	4.6	3.4	1.4	0.3
7	5.0	3.4	1.5	0.2
8	4.4	2.9	1.4	0.2
9	4.9	3.1	1.5	0.1

PROGRAM 2

Date:05-04-2024

Demonstrate various data pre-processing techniques for a given dataset

Date__/__/__
Page____

5/4/24

Week - 2

Demonstrate various Data preprocessing techniques for a given dataset.

Algorithm

1) Import dataset using pandas.

2) Do dataset.head( ) , dataset.shape( ) to see the dataset's first 5 rows.

3) Use isnull( ) function to check null values.

4) Drop or fill missing values according to use case.
   Ex:- drop_na( ) and ffill( ).

5) use scikit learn ~~libraries~~ to perform more preprocessing if ~~required~~.

PROGRAM 3

Date:12-04-2024

Use an appropriate data set for building the decision tree (ID3) and apply

this knowledge to classify a new sample

Algorithm:

12/4/24

Date __/__/__
Page ____

Week - 3

Use an appropriate dataset for building the decision tree (ID3) and apply this knowledge to classify a new sample.

Algorithm:

ID3 (Examples, Target-attribute)

If all examples are in the same class, return a leaf node with that class label.

If the list of attributes is empty, return a leaf node with the most common class.

Choose the best attribute A to split on using entropy and information gain.

Entropy of the entire dataset,

$S\{+,-\} = -P_{\oplus} \log_2 P_{\oplus} - P_{\ominus} \log_2 P_{\ominus}$

Information gain = entropy (parent) $- \left(\sum_{i=1}^{n} \text{Weighted average} \right.$ of $\left. \text{Entropy}(\text{child}_i) \right)$

for each possible value v of A:

Add a new branch below the decision node for value v

Let examples-v be subset of examples with value v for attribute A

if examples-v is empty:

Add a leaf node with the most common class label in Examples to this branch.

Else:

Recursively call ID3 (Examples-v, Target Attribute)

Code:

Importing Database

```
In [2]:
# Importing the required libraries
import pandas as pd
import numpy as np
import math

# Reading the dataset (Tennis-dataset)
data = pd.read_csv('/content/PlayTennis.csv')
```

```
In [ ]:
from google.colab import drive
drive.mount('/content/drive')
```

```
In [3]:
def highlight(cell_value):
    '''
    Highlight yes / no values in the dataframe
    '''
    color_1 = 'background-color: pink;'
    color_2 = 'background-color: lightgreen;'

    if cell_value == 'no':
        return color_1
    elif cell_value == 'yes':
        return color_2

data.style.applymap(highlight)\
    .set_properties(subset=data.columns, **{'width': '100px'})\
    .set_table_styles([{'selector': 'th', 'props': [('background-color', 'lightgray'), ('border', '1px solid gray'),
                                                     ('font-weight', 'bold')]},
     {'selector': 'tr:hover', 'props': [('background-color', 'white'), ('border', '1.5px solid black')]}])
```

Out[3]:

	outlook	temp	humidity	windy	play
0	sunny	hot	high	False	no
1	sunny	hot	high	True	no
2	overcast	hot	high	False	yes
3	rainy	mild	high	False	yes
4	rainy	cool	normal	False	yes
5	rainy	cool	normal	True	no
6	overcast	cool	normal	True	yes
7	sunny	mild	high	False	no
8	sunny	cool	normal	False	yes
9	rainy	mild	normal	False	yes
10	sunny	mild	normal	True	yes
11	overcast	mild	high	True	yes
12	overcast	hot	normal	False	yes
13	rainy	mild	high	True	no

Entropy of the dataset

In [4]:

```
def find_entropy(data):
    """
    Returns the entropy of the class or features
    formula: - ∑ P(X)logP(X)
    """
    entropy = 0
    for i in range(data.nunique()):
        x = data.value_counts()[i]/data.shape[0]
        entropy += (- x * math.log(x,2))
    return round(entropy,3)



def information_gain(data, data_):
    """
    Returns the information gain of the features
    """
    info = 0
    for i in range(data_.nunique()):
        df = data[data_ == data_.unique()[i]]
        w_avg = df.shape[0]/data.shape[0]
        entropy = find_entropy(df.play)
        x = w_avg * entropy
        info += x
    ig = find_entropy(data.play) - info
    return round(ig, 3)



def entropy_and_infogain(datax, feature):
    """
    Grouping features with the same class and computing their
    entropy and information gain for splitting
    """
    for i in range(data[feature].nunique()):
        df = datax[datax[feature]==data[feature].unique()[i]]
        if df.shape[0] < 1:
            continue

        display(df[[feature, 'play']].style.applymap(highlight)\
                .set_properties(subset=[feature, 'play'], **{'width': '80px'})\
                .set_table_styles([{'selector': 'th', 'props': [('background-color', 'lightgray'),
                                                                ('border', '1px solid gray'),
                                                                ('font-weight', 'bold')]},
                                   {'selector': 'td', 'props': [('border', '1px solid gray')]},
                                   {'selector': 'tr:hover', 'props': [('background-color', 'white'),
                                                                      ('border', '1.5px solid black')]}]))

        print(f'Entropy of {feature} - {data[feature].unique()[i]} = {find_entropy(df.play)}')
    print(f'Information Gain for {feature} = {information_gain(datax, datax[feature])}')
```

In [5]:

```
print(f'Entropy of the entire dataset: {find_entropy(data.play)}')
```

```
Entropy of the entire dataset: 0.94
```

Entropy and Information Gain of temperature

In [6]:
```
entropy_and_infogain(data, 'temp')
```

	temp	play
0	hot	no
1	hot	no
2	hot	yes
12	hot	yes

```
Entropy of temp - hot = 1.0
```

	temp	play
3	mild	yes
7	mild	no
9	mild	yes
10	mild	yes
11	mild	yes
13	mild	no

```
Entropy of temp - mild = 0.918
```

	temp	play
4	cool	yes
5	cool	no
6	cool	yes
8	cool	yes

```
Entropy of temp - cool = 0.811
Information Gain for temp = 0.029
```

Entropy and Information Gain of humidity

In [7]:
```
entropy_and_infogain(data, 'humidity')
```

	humidity	play
0	high	no
1	high	no
2	high	yes
3	high	yes
7	high	no
11	high	yes
13	high	no

```
Entropy of humidity - high = 0.985
```

	humidity	play
4	normal	yes
5	normal	no
6	normal	yes
8	normal	yes
9	normal	yes
10	normal	yes
12	normal	yes

```
Entropy of humidity - normal = 0.592
Information Gain for humidity = 0.151
```

Entropy and Information Gain of windy

In [8]:

```
entropy_and_infogain(data, 'windy')
```

	windy	play
0	False	no
2	False	yes
3	False	yes
4	False	yes
7	False	no
8	False	yes
9	False	yes
12	False	yes

```
Entropy of windy - False = 0.811
```

	windy	play
1	True	no
5	True	no
6	True	yes
10	True	yes
11	True	yes
13	True	no

```
Entropy of windy - True = 1.0
Information Gain for windy = 0.048
```

Rainy Outlook

Rainy -outlook

In [9]:
```
rainy = data[data['outlook'] == 'rainy']
rainy.style.applymap(highlight)\
    .set_properties(subset=data.columns, **{'width': '100px'})\
    .set_table_styles([{'selector': 'th', 'props': [('background-color', 'lightgray'), ('border', '1px solid gray'),
                                                    ('font-weight', 'bold')]},
     {'selector': 'tr:hover', 'props': [('background-color', 'white'), ('border', '1.5px solid black')]}])
```

Out[9]:

	outlook	temp	humidity	windy	play
3	rainy	mild	high	False	yes
4	rainy	cool	normal	False	yes
5	rainy	cool	normal	True	no
9	rainy	mild	normal	False	yes
13	rainy	mild	high	True	no

In [10]:
```
print(f'Entropy of the Rainy dataset: {find_entropy(rainy.play)}')
```

```
Entropy of the Rainy dataset: 0.971
```

In [11]:
```
entropy_and_infogain(rainy, 'temp')
```

	temp	play
3	mild	yes
9	mild	yes
13	mild	no

```
Entropy of temp - mild = 0.918
```

	temp	play
4	cool	yes
5	cool	no

```
Entropy of temp - cool = 1.0
Information Gain for temp = 0.02
```

In [12]:
```
entropy_and_infogain(rainy, 'humidity')
```

	humidity	play
3	high	yes
13	high	no

```
Entropy of humidity - high = 1.0
```

	humidity	play
4	normal	yes
5	normal	no
9	normal	yes

```
Entropy of humidity - normal = 0.918
Information Gain for humidity = 0.02
```

In [13]:
```
entropy_and_infogain(rainy, 'windy')
```

	windy	play
3	False	yes
4	False	yes
9	False	yes

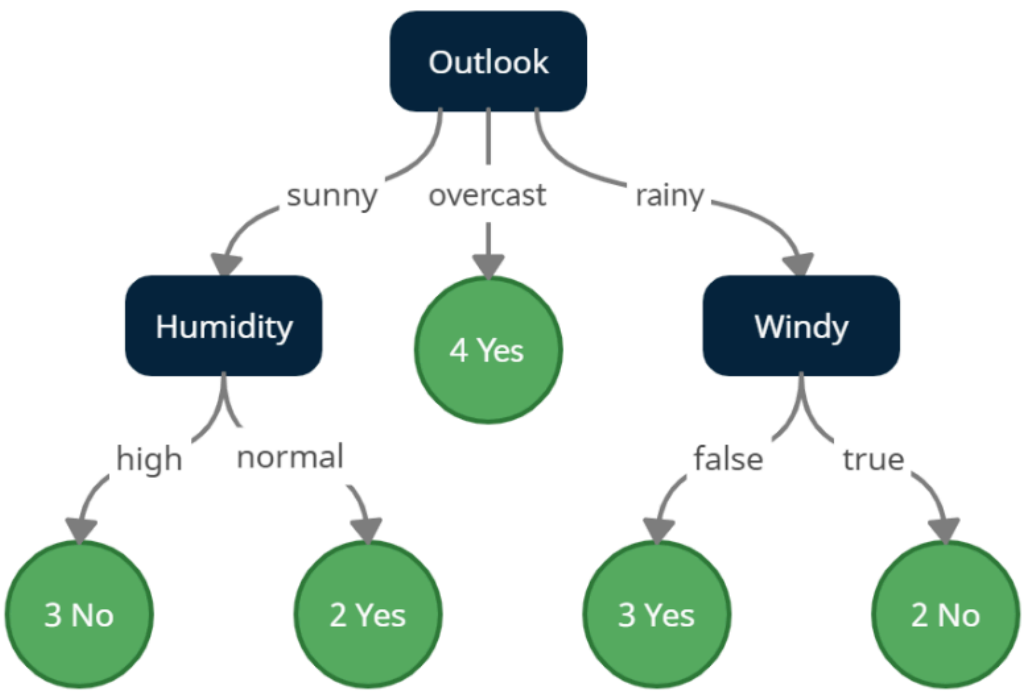
```
Entropy of windy - False = 0.0
```

	windy	play
5	True	no
13	True	no

```
Entropy of windy - True = 0.0
Information Gain for windy = 0.971
```

wind has highest information gain

Output



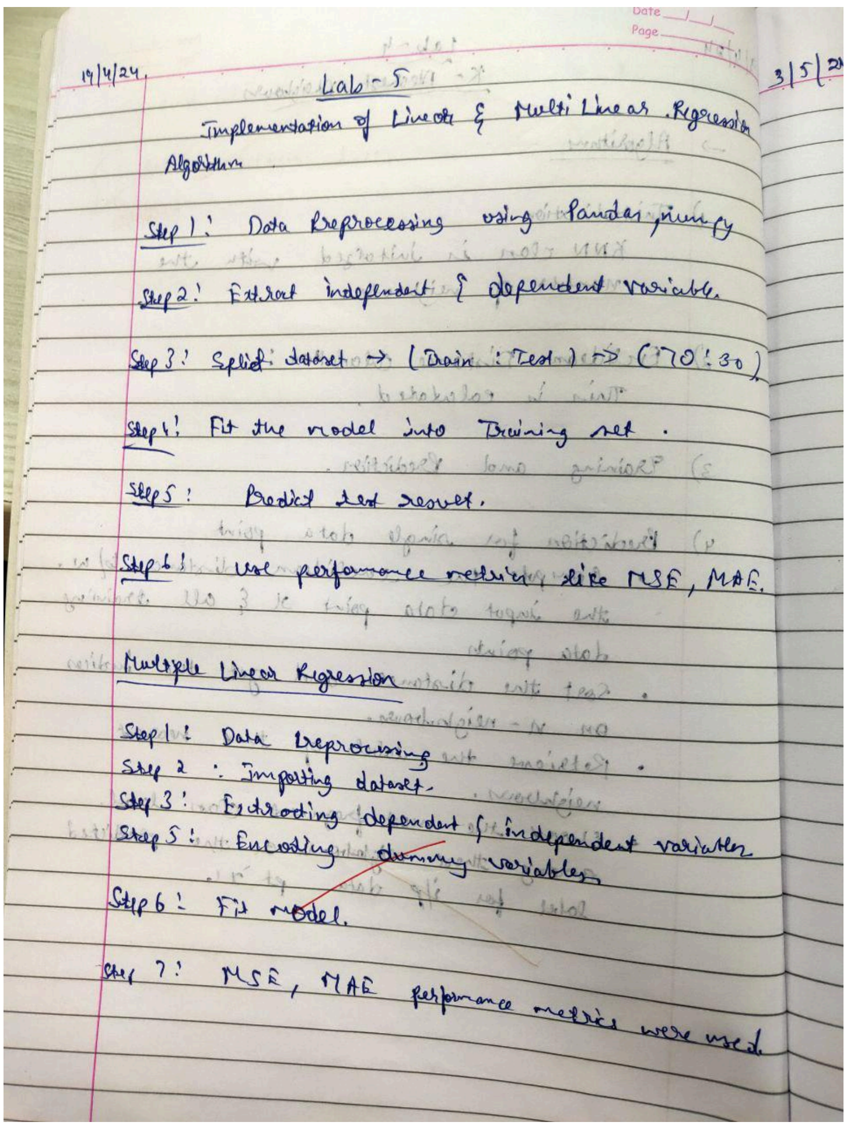
PROGRAM 4

Date:19-04-2024

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset

LINEAR REGRESSION:

Algorithm



19/4/24.

Lab-5

Implementation of Linear & Multi Linear Regression Algorithm.

Step 1: Data Preprocessing using Pandas, numpy

Step 2: Extract independent & dependent variable.

Step 3: Split dataset → (Train : Test) → (70:30)

Step 4: Fit the model into Training set.

Step 5: Predict test result.

Step 6: Use performance metrics like MSE, MAE.

Multiple Linear Regression

Step 1: Data Preprocessing

Step 2: Importing dataset.

Step 3: Extracting dependent & independent variables

Step 5: Encoding dummy variables

Step 6: Fit model.

Step 7: MSE, MAE performance metrics were used.

3/5/24

Code

Linear Regression

In [2]:
```
import pandas as pd
```

In [35]:
```
salary = pd.read_csv('https://github.com/ybifoundation/Dataset/raw/main/Salary%20Data.csv')
```

In [36]:
```
y = salary['Salary']
```

In [37]:
```
X = salary[['Experience Years']]
```

In [38]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y, train_size=0.7, random_state=2529)
```

In [39]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[39]:
```
((28, 1), (12, 1), (28,), (12,))
```

In [40]:
```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
```

In [41]:
```
model.fit(X_train,y_train)
```

Out[41]:
```
LinearRegression()
```
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [42]:
```
model.coef_
```

Out[42]:
```
array([9405.62])
```

In [43]:
```
y_pred = model.predict(X_test)
```

In [44]:
```
y_pred
```

Out[44]:
```
array([ 90555.15,  59516.62, 106544.7 ,  64219.43,  68922.24, 123474.81,
        84911.78,  63278.87,  65159.99,  61397.74,  37883.7 ,  50111.  ])
```

In [45]:
```
from sklearn.metrics import mean_absolute_error, mean_absolute_percentage_error, mean_squared_error
```

In [16]:
```
import numpy as np
```

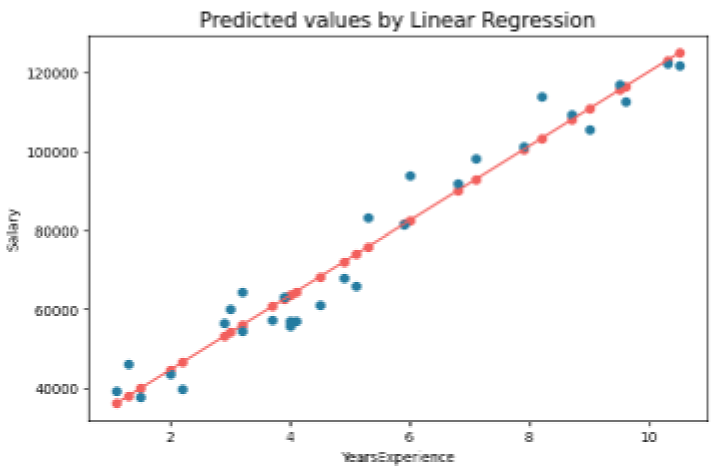
In [46]:
```
mean_absolute_error(y_test,y_pred)
```

Out[46]:
```
4005.9263101681768
```

Output

```
In [26]: print("Coefficients:\n=============")
         print("b0 : ", b0)
         print("b1 : ", b1)
```

```
Coefficients:
=============
b0 :  25792.20019866869
b1 :  9449.962321455077
```



MULTIPLE LINEAR REGRESSION:

Code

In [19]:
```
house = pd.read_csv('https://github.com/YBIFoundation/Dataset/raw/main/Boston.csv')
```

In [20]:
```
house.head()
```

Out[20]:

	CRIM	ZN	INDUS	CHAS	NX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296.0	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242.0	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242.0	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222.0	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222.0	18.7	396.90	5.33	36.2

In [21]:
```
house.describe()
```

Out[21]:

	CRIM	ZN	INDUS	CHAS	NX	RM	AGE	DIS	RAD	TAX	PTRAT
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.0000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407	408.237154	18.4555
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.537116	2.1649
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.6000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.000000	17.4000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.000000	19.0500
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.000000	20.2000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.0000

In [22]:
```
house.columns
```

Out[22]:
```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX',
       'PTRATIO', 'B', 'LSTAT', 'MEDV'],
      dtype='object')
```

In [23]:
```
y = house['MEDV']
```

In [24]:
```
X = house.drop(['MEDV'],axis=1)
```

In [25]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y, train_size=0.7, random_state=2529)
```

In [26]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[26]:
```
((354, 13), (152, 13), (354,), (152,))
```

In [25]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y, train_size=0.7, random_state=2529)
```

In [26]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[26]:
```
((354, 13), (152, 13), (354,), (152,))
```

In [27]:
```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
```

In [28]:
```
# Step 6 : train or fit model
model.fit(X_train,y_train)
```

Out[28]:
```
LinearRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [29]:
```
model.intercept_
```

Out[29]:
```
34.21916368862993
```

In [30]:
```
model.coef_
```

Out[30]:
```
array([-1.29e-01,  3.65e-02,  1.54e-02,  2.35e+00, -2.04e+01,  4.41e+00,
        4.61e-03, -1.59e+00,  2.51e-01, -9.60e-03, -9.64e-01,  1.01e-02,
       -5.43e-01])
```

In [31]:
```
# Step 7 : predict model
y_pred = model.predict(X_test)
```

Output

In [32]:
```
y_pred
```

Out[32]:
```
array([31.72, 22.02, 21.17, 39.78, 20.1 , 22.86, 18.36, 14.79, 22.56,
       21.35, 18.38, 27.97, 29.86,  6.45, 10.68, 26.25, 21.89, 25.23,
        3.62, 36.22, 24.08, 22.94, 14.27, 20.79, 24.23, 16.74, 18.75,
       20.97, 28.51, 20.86,  9.23, 17.07, 22.07, 22.23, 39.26, 26.17,
       42.5 , 19.35, 34.52, 14.07, 13.81, 23.28, 11.79,  9.01, 21.65,
       25.55, 18.17, 16.82, 14.66, 14.86, 33.79, 33.27, 15.49, 24.08,
       27.64, 19.58, 45.02, 20.97, 20.07, 27.67, 34.59, 12.71, 23.66,
       31.66, 28.97, 32.46, 13.93, 35.49, 19.36, 19.6 ,  1.44, 24.1 ,
       33.67, 20.62, 26.89, 21.29, 31.95, 29.74, 13.93, 13.82, 19.76,
       21.54, 20.87, 23.63, 28.8 , 23.64,  6.95, 22.2 , -6.82, 16.97,
       16.77, 25.44, 14.95,  3.72, 15.03, 16.91, 21.46, 31.66, 30.72,
       23.73, 22.19, 13.76, 18.47, 18.15, 36.6 , 27.49, 11.  , 17.26,
       22.49, 16.53, 29.49, 22.89, 24.68, 20.38, 19.69, 22.55, 27.32,
       24.86, 20.2 , 29.14,  7.43,  5.85, 25.35, 38.73, 23.94, 25.28,
       20.11, 19.75, 25.07, 35.16, 27.32, 27.26, 31.4 , 16.55, 14.3 ,
       23.77,  7.65, 23.35, 21.37, 26.12, 25.32, 13.12, 17.67, 36.2 ,
       20.5 , 27.95, 22.46, 18.15, 31.24, 20.85, 27.36, 30.53])
```

In [33]:
```
# Step 8 : model accuracy
from sklearn.metrics import mean_absolute_error, mean_absolute_percentage_error, mean_squared_error
```

In [34]:
```
mean_absolute_error(y_test,y_pred)
```

Out[34]:
```
3.155030927602485
```

PROGRAM 5

Date:26-04-2024

Build Logistic Regression Model for a given dataset

Algorithm

Lab 6

Implementation of Logistic Regression

Algorithm

1. Initialization of parameters.
   ↳ weights 'w', bias as 'b' to zeros.
   parameters are starting with neutral point
2. Forward propagation.
   Apply sigmoid activation function.
3. Compute cost
   using binary cross entropy loss function
4. Backward propagation & parameter update.
5. Repeat 2-5.
6. Prediction.

Output:-

Training accuracy of 80% in first iteration.

3/5/2024

Code

In [2]:

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
# Input data files are available in the "../input/" directory.
# For example, running this (by clicking run or pressing Shift+Enter) will list the files in the input directory

import os
```

In [4]:

```
data = pd.read_csv('/content/data.csv')
```

In [5]:

```
data.drop(['Unnamed: 32',"id"], axis=1, inplace=True)
data.diagnosis = [1 if each == "M" else 0 for each in data.diagnosis]
y = data.diagnosis.values
x_data = data.drop(['diagnosis'], axis=1)
```

In [7]:

```
# Assuming x_data is a numpy array or pandas DataFrame
x = (x_data - np.min(x_data)) / (np.max(x_data) - np.min(x_data))
```

In [8]:

```
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.15, random_state=42)

x_train = x_train.T
x_test = x_test.T
y_train = y_train.T
y_test = y_test.T

print("x train: ",x_train.shape)
print("x test: ",x_test.shape)
print("y train: ",y_train.shape)
print("y test: ",y_test.shape)
```

```
x train:  (30, 483)
x test:  (30, 86)
y train:  (483,)
y test:  (86,)
```

In [9]:

```
def initialize_weights_and_bias(dimension):
    w = np.full((dimension,1),0.01)
    b = 0.0
    return w, b
```

In [10]:

```
def sigmoid(z):
    y_head = 1/(1+np.exp(-z))
    return y_head
```

In [ ]:

```
def forward_backward_propagation(w,b,x_train,y_train):
    # forward propagation
    z = np.dot(w.T,x_train) + b
    y_head = sigmoid(z)
    loss = -y_train*np.log(y_head)-(1-y_train)*np.log(1-y_head)
    cost = (np.sum(loss))/x_train.shape[1]      # x_train.shape[1]  is for scaling
    # backward propagation
    derivative_weight = (np.dot(x_train,((y_head-y_train).T)))/x_train.shape[1] # x_train.shape[1]  is for scaling
    derivative_bias = np.sum(y_head-y_train)/x_train.shape[1]                 # x_train.shape[1]  is for scaling
    gradients = {"derivative_weight": derivative_weight,"derivative_bias": derivative_bias}
    return cost,gradients
```

In [ ]:

```
def update(w, b, x_train, y_train, learning_rate,number_of_iterarion):
    cost_list = []
    cost_list2 = []
    index = []
    # updating(learning) parameters is number_of_iterarion times
    for i in range(number_of_iterarion):
        # make forward and backward propagation and find cost and gradients
        cost,gradients = forward_backward_propagation(w,b,x_train,y_train)
        cost_list.append(cost)
        w = w - learning_rate * gradients["derivative_weight"]
        b = b - learning_rate * gradients["derivative_bias"]
        if i % 10 == 0:
            cost_list2.append(cost)
            index.append(i)
            print ("Cost after iteration %i: %f" %(i, cost))
    # we update(learn) parameters weights and bias
    parameters = {"weight": w,"bias": b}
    plt.plot(index,cost_list2)
    plt.xticks(index,rotation='vertical')
    plt.xlabel("Number of Iterarion")
    plt.ylabel("Cost")
    plt.show()
    return parameters, gradients, cost_list
```

In [11]:

```
def predict(w,b,x_test):
    # x_test is a input for forward propagation
    z = sigmoid(np.dot(w.T,x_test)+b)
    Y_prediction = np.zeros((1,x_test.shape[1]))
    # if z is bigger than 0.5, our prediction is sign one (y_head=1),
    # if z is smaller than 0.5, our prediction is sign zero (y_head=0),
    for i in range(z.shape[1]):
        if z[0,i]<= 0.5:
            Y_prediction[0,i] = 0
        else:
            Y_prediction[0,i] = 1

    return Y_prediction
```

In [18]:

```
def sigmoid(z):
    return 1 / (1 + np.exp(-z))

def initialize_weights_and_bias(dim):
    w = np.zeros((dim, 1))
    b = 0
    return w, b

def compute_cost(w, b, x, y):
    m = x.shape[1]
    A = sigmoid(np.dot(w.T, x) + b)
    cost = -1 / m * np.sum(y * np.log(A) + (1 - y) * np.log(1 - A))
    return cost

def propagate(w, b, x, y):
    m = x.shape[1]
    A = sigmoid(np.dot(w.T, x) + b)
    dw = 1 / m * np.dot(x, (A - y).T)
    db = 1 / m * np.sum(A - y)
    return dw, db
```

```python
def logistic_regression(x_train, y_train, x_test, y_test, learning_rate, num_iterations):
    # Initialize
    dimension = x_train.shape[0]  # Number of features
    w, b = initialize_weights_and_bias(dimension)
    costs = []

    # Gradient Descent
    for i in range(num_iterations):
        # Forward and Backward Propagation
        dw, db = propagate(w, b, x_train, y_train)

        # Update parameters
        w -= learning_rate * dw
        b -= learning_rate * db

        # Record the costs
        if i % 100 == 0:
            cost = compute_cost(w, b, x_train, y_train)
            costs.append(cost)
            print(f"Cost after iteration {i}: {cost}")

    # Evaluate model
    y_prediction_train = predict(w, b, x_train)
    y_prediction_test = predict(w, b, x_test)

    train_accuracy = 100 - np.mean(np.abs(y_prediction_train - y_train)) * 100
    test_accuracy = 100 - np.mean(np.abs(y_prediction_test - y_test)) * 100

    print("Train accuracy: {} %".format(train_accuracy))
    print("Test accuracy: {} %".format(test_accuracy))

    return w, b

# Assuming you have defined the predict function
# def predict(w, b, x):
#     ...

# Assuming you have defined x_train, y_train, x_test, y_test, learning_rate, and num_iterations
logistic_regression(x_train, y_train, x_test, y_test, learning_rate=1, num_iterations=100)
```

Output

```
Cost after iteration 0: 0.6782740160052536
Train accuracy: 80.7453416149068З %
Test accuracy: 81.3953488372093 %

Out[18]: (array([[ 1.77806654e-02],
                [ 1.10160388e-02],
                [ 1.27806976e-01],
                [ 1.95749649e+00],
                [ 1.85931875e-05],
                [ 2.68863405e-04],
                [ 4.89020048e-04],
                [ 2.63106803e-04],
                [ 3.49357933e-05],
                [-2.02145931e-05],
                [ 1.25690784e-03],
                [-3.98285024e-04],
                [ 8.96937014e-03],
                [ 2.02426962e-01],
                [-3.60718647e-06],
                [ 4.19150446e-05],
                [ 6.03411729e-05],
                [ 2.00740406e-05],
                [-6.24803672e-06],
                [ 6.24944780e-07],
                [ 2.79506973e-02],
                [ 1.99326360e-02],
                [ 1.98774929e-01],
                [ 3.39189908e+00],
                [ 5.79135019e-05],
                [ 8.53041205e-04],
                [ 1.25862280e-03],
                [ 4.60695564e-04],
                [ 1.89671301e-04],
                [ 3.52490835e-05]]),
          -1.5161875221606185)
```

PROGRAM 6

Date:26-04-2024

Build KNN Classification model for a given dataset.

Algorithm

19/4/24

Lab - 4

K - Nearest Neighbours

→ Algorithm

1) Initialization :
   KNN class is initialized with the numbers of neighbours.

2) Euclidean Distance calculation :
   This is calculated.

3) Training and Prediction.

4) Prediction for single data point
   - Compute the euclidean distance b/w the input data point x & all training data points
   - Sort the distances and get the indices on n - neighbours.
   - Retrieve the labels of these nearest neighbours.
   - Choose the most frequent class label among these neighbours as the predicted label for i/p data pt 'x'.

Code

In [1]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt # for data visualization purposes
import seaborn as sns # for data visualization
%matplotlib inline
```

In [2]:
```
data = '/content/cancer_detector.txt'
df = pd.read_csv(data, header=None)
```

In [3]:
```
df.shape
```

Out[3]:
```
(699, 11)
```

In [4]:
```
col_names = ['Id', 'Clump_thickness', 'Uniformity_Cell_Size', 'Uniformity_Cell_Shape', 'Marginal_Adhesion',
             'Single_Epithelial_Cell_Size', 'Bare_Nuclei', 'Bland_Chromatin', 'Normal_Nucleoli', 'Mitoses', 'Class']

df.columns = col_names

df.columns
```

Out[4]:
```
Index(['Id', 'Clump_thickness', 'Uniformity_Cell_Size',
       'Uniformity_Cell_Shape', 'Marginal_Adhesion',
       'Single_Epithelial_Cell_Size', 'Bare_Nuclei', 'Bland_Chromatin',
       'Normal_Nucleoli', 'Mitoses', 'Class'],
      dtype='object')
```

In [5]:
```
df.head()
```

Out[5]:

	Id	Clump_thickness	Uniformity_Cell_Size	Uniformity_Cell_Shape	Marginal_Adhesion	Single_Epithelial_Cell_Size	Bare_Nuclei	Bla
0	1000025	5	1	1	1	2	1	
1	1002945	5	4	4	5	7	10	
2	1015425	3	1	1	1	2	2	
3	1016277	6	8	8	1	3	4	
4	1017023	4	1	1	3	2	1	

In [18]:
```
import numpy as np
```

In [21]:
```
# view summary statistics in numerical variables

print(round(df.describe(),2))
```

```
       Clump_thickness  Uniformity_Cell_Size  Uniformity_Cell_Shape  \
count           699.00                699.00                 699.00
mean              4.42                  3.13                   3.21
std               2.82                  3.05                   2.97
min               1.00                  1.00                   1.00
25%               2.00                  1.00                   1.00
50%               4.00                  1.00                   1.00
75%               6.00                  5.00                   5.00
max              10.00                 10.00                  10.00

       Marginal_Adhesion  Single_Epithelial_Cell_Size  Bare_Nuclei  \
count             699.00                       699.00       683.00
mean                2.81                         3.22         3.54
std                 2.86                         2.21         3.64
min                 1.00                         1.00         1.00
25%                 1.00                         2.00         1.00
50%                 1.00                         2.00         1.00
75%                 4.00                         4.00         6.00
max                10.00                        10.00        10.00

       Bland_Chromatin  Normal_Nucleoli  Mitoses   Class
count           699.00           699.00   699.00  699.00
mean              3.44             2.87     1.59    2.69
std               2.44             3.05     1.72    0.95
min               1.00             1.00     1.00    2.00
25%               2.00             1.00     1.00    2.00
50%               3.00             1.00     1.00    2.00
75%               5.00             4.00     1.00    4.00
max              10.00            10.00    10.00    4.00
```

In [22]:
```
X = df.drop(['Class'], axis=1)

y = df['Class']
```

In [23]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)
```

In [24]:
```
X_train.shape, X_test.shape
```

Out[24]:
```
((559, 9), (140, 9))
```

In [25]:
```
for col in X_train.columns:
    if X_train[col].isnull().mean()>0:
        print(col, round(X_train[col].isnull().mean(),4))
```

```
Bare_Nuclei 0.0233
```

In [26]:
```
for df1 in [X_train, X_test]:
    for col in X_train.columns:
        col_median=X_train[col].median()
        df1[col].fillna(col_median, inplace=True)
```

In [27]:
```
cols = X_train.columns
```

In [28]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

X_train = scaler.fit_transform(X_train)

X_test = scaler.transform(X_test)
```

In [29]:
```
X_train = pd.DataFrame(X_train, columns=[cols])
```

In [30]:
```
X_test = pd.DataFrame(X_test, columns=[cols])
```

Output

```
In [33]: y_pred = knn.predict(X_test)

         y_pred
```

```
Out[33]: array([2, 2, 4, 2, 4, 2, 4, 2, 4, 2, 2, 2, 4, 4, 4, 2, 2, 4, 4, 2, 4, 4,
                2, 2, 2, 4, 2, 2, 4, 4, 2, 2, 2, 2, 2, 2, 2, 4, 2, 2, 2, 2, 2, 2,
                4, 4, 2, 4, 2, 4, 4, 2, 2, 4, 2, 2, 2, 2, 2, 2, 4, 2, 2, 4, 4, 4,
                4, 2, 2, 4, 2, 2, 4, 4, 2, 2, 2, 2, 4, 2, 2, 2, 4, 2, 2, 2, 4, 2,
                4, 4, 2, 2, 2, 4, 2, 2, 2, 4, 2, 4, 4, 2, 2, 2, 4, 2, 2, 2, 2, 2,
                4, 4, 4, 2, 2, 2, 2, 2, 4, 4, 4, 4, 2, 4, 2, 2, 4, 4, 4, 4, 4, 2,
                2, 4, 4, 2, 2, 4, 2, 2])
```

```
In [34]: knn.predict_proba(X_test)[:,0]
```

```
Out[34]: array([1.        , 1.        , 0.33333333, 1.        , 0.        ,
                1.        , 0.        , 1.        , 0.        , 0.66666667,
                1.        , 1.        , 0.        , 0.33333333, 0.        ,
                1.        , 1.        , 0.        , 0.        , 1.        ,
                0.        , 0.        , 1.        , 1.        , 1.        ,
                0.        , 1.        , 1.        , 0.        , 0.        ,
                1.        , 1.        , 1.        , 1.        , 1.        ,
                0.66666667, 1.        , 0.        , 1.        , 1.        ,
                1.        , 1.        , 1.        , 1.        , 0.        ,
                0.        , 1.        , 0.        , 1.        , 0.        ,
                0.        , 1.        , 1.        , 0.        , 1.        ,
                1.        , 1.        , 1.        , 0.66666667, 1.        ,
                0.        , 1.        , 1.        , 0.        , 0.        ,
                0.33333333, 0.        , 1.        , 1.        , 0.        ,
                1.        , 1.        , 0.        , 0.        , 1.        ,
                1.        , 1.        , 1.        , 0.        , 1.        ,
                1.        , 1.        , 0.        , 1.        , 1.        ,
                1.        , 0.        , 1.        , 0.        , 0.        ,
                1.        , 1.        , 0.66666667, 0.        , 1.        ,
                1.        , 1.        , 0.        , 1.        , 0.        ,
                0.        , 1.        , 1.        , 1.        , 0.        ,
                1.        , 1.        , 1.        , 1.        , 1.        ,
                0.        , 0.33333333, 0.        , 1.        , 1.        ,
                1.        , 1.        , 1.        , 0.        , 0.        ,
                0.        , 0.33333333, 1.        , 0.        , 1.        ,
                1.        , 0.33333333, 0.33333333, 0.        , 0.        ,
                0.        , 1.        , 1.        , 0.33333333, 0.        ,
                1.        , 1.        , 0.        , 1.        , 1.        ])
```

```
In [35]: from sklearn.metrics import accuracy_score

         print('Model accuracy score: {0:0.4f}'. format(accuracy_score(y_test, y_pred)))
```

```
Model accuracy score: 0.9714
```

```
In [36]: y_pred_train = knn.predict(X_train)
```

```
In [37]: print('Training-set accuracy score: {0:0.4f}'. format(accuracy_score(y_train, y_pred_train)))
```

```
Training-set accuracy score: 0.9821
```

PROGRAM 7

Date:24-05-2024

Build Support vector machine model for a given dataset

Algorithm

24/5/24.

Lab-9

SVM (support vector machine)

① Define the Kernal function.
Ex:- $K(x_1, x_2) = x_1 \cdot x_2$.

② Solve the quadractic programming (QP) problem to find the value of 'α'.

③ Compute the weight and bias.

④ Identify the support vector.

⑤ make predictions.

Output:-

```
model = SVM().
model.fit (X_train, Y_train)
predictions = model.predict (X_test).
accuracy (y_test, predictions).

model.predict ([[-0.47, -0.16, -0.448, ...
    -- 0.1969]])
```

Code

Open in Colab

In [ ]:

```
import seaborn as sns
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import plotly.express as px
```

In [ ]:

```
df = pd.read_csv('/content/breast-cancer.csv')
df.head()
```

Out[ ]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mea
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.300
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.086
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.197
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.241
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.198

5 rows × 32 columns

In [ ]:

```
df.drop('id', axis=1, inplace=True) #drop redundant columns
```

In [ ]:

```
df.describe().T
```

Out[ ]:

	count	mean	std	min	25%	50%	75%	max
radius_mean	569.0	14.127292	3.524049	6.981000	11.700000	13.370000	15.780000	28.11000
texture_mean	569.0	19.289649	4.301036	9.710000	16.170000	18.840000	21.800000	39.28000
perimeter_mean	569.0	91.969033	24.298981	43.790000	75.170000	86.240000	104.100000	188.50000
area_mean	569.0	654.889104	351.914129	143.500000	420.300000	551.100000	782.700000	2501.00000
smoothness_mean	569.0	0.096360	0.014064	0.052630	0.086370	0.095870	0.105300	0.16340
compactness_mean	569.0	0.104341	0.052813	0.019380	0.064920	0.092630	0.130400	0.34540
concavity_mean	569.0	0.088799	0.079720	0.000000	0.029560	0.061540	0.130700	0.42680
concave points_mean	569.0	0.048919	0.038803	0.000000	0.020310	0.033500	0.074000	0.20120
symmetry_mean	569.0	0.181162	0.027414	0.106000	0.161900	0.179200	0.195700	0.30400
fractal_dimension_mean	569.0	0.062798	0.007060	0.049960	0.057700	0.061540	0.066120	0.09744
radius_se	569.0	0.405172	0.277313	0.111500	0.232400	0.324200	0.478900	2.87300
texture_se	569.0	1.216853	0.551648	0.360200	0.833900	1.108000	1.474000	4.88500
perimeter_se	569.0	2.866059	2.021855	0.757000	1.606000	2.287000	3.357000	21.98000
area_se	569.0	40.337079	45.491006	6.802000	17.850000	24.530000	45.190000	542.20000
smoothness_se	569.0	0.007041	0.003003	0.001713	0.005169	0.006380	0.008146	0.03113
compactness_se	569.0	0.025478	0.017908	0.002252	0.013080	0.020450	0.032450	0.13540
concavity_se	569.0	0.031894	0.030186	0.000000	0.015090	0.025890	0.042050	0.39600
concave points_se	569.0	0.011796	0.006170	0.000000	0.007638	0.010930	0.014710	0.05279
symmetry_se	569.0	0.020542	0.008266	0.007882	0.015160	0.018730	0.023480	0.07895
fractal_dimension_se	569.0	0.003795	0.002646	0.000895	0.002248	0.003187	0.004558	0.02984
radius_worst	569.0	16.269190	4.833242	7.930000	13.010000	14.970000	18.790000	36.04000
texture_worst	569.0	25.677223	6.146258	12.020000	21.080000	25.410000	29.720000	49.54000
perimeter_worst	569.0	107.261213	33.602542	50.410000	84.110000	97.660000	125.400000	251.20000
area_worst	569.0	880.583128	569.356993	185.200000	515.300000	686.500000	1084.000000	4254.00000
smoothness_worst	569.0	0.132369	0.022832	0.071170	0.116600	0.131300	0.146000	0.22260
compactness_worst	569.0	0.254265	0.157336	0.027290	0.147200	0.211900	0.339100	1.05800
concavity_worst	569.0	0.272188	0.208624	0.000000	0.114500	0.226700	0.382900	1.25200
concave points_worst	569.0	0.114606	0.065732	0.000000	0.064930	0.099930	0.161400	0.29100
symmetry_worst	569.0	0.290076	0.061867	0.156500	0.250400	0.282200	0.317900	0.66380
fractal_dimension_worst	569.0	0.083946	0.018061	0.055040	0.071460	0.080040	0.092080	0.20750

In [ ]:

```
df['diagnosis'] = (df['diagnosis'] == 'M').astype(int) #encode the label into 1/0
```

In [ ]:

```
corr = df.corr()
```

In [ ]:

```
# Get the absolute value of the correlation
cor_target = abs(corr["diagnosis"])

# Select highly correlated features (thresold = 0.2)
relevant_features = cor_target[cor_target>0.2]

# Collect the names of the features
names = [index for index, value in relevant_features.items()]

# Drop the target variable from the results
names.remove('diagnosis')

# Display the results
print(names)
```

```
['radius_mean', 'texture_mean', 'perimeter_mean', 'area_mean', 'smoothness_mean', 'compactness_mean', 'concavity_mean', 'conc
ave points_mean', 'symmetry_mean', 'radius_se', 'perimeter_se', 'area_se', 'compactness_se', 'concavity_se', 'concave points_
se', 'radius_worst', 'texture_worst', 'perimeter_worst', 'area_worst', 'smoothness_worst', 'compactness_worst', 'concavity_wo
rst', 'concave points_worst', 'symmetry_worst', 'fractal_dimension_worst']
```

In [ ]:

```
X = df[names].values
y = df['diagnosis']
```

In [ ]:

```
def scale(X):
    """
    Standardizes the data in the array X.

    Parameters:
        X (numpy.ndarray): Features array of shape (n_samples, n_features).

    Returns:
        numpy.ndarray: The standardized features array.
    """
    # Calculate the mean and standard deviation of each feature
    mean = np.mean(X, axis=0)
    std = np.std(X, axis=0)

    # Standardize the data
    X = (X - mean) / std
    return X
```

In [ ]:

```
X = scale(X)
```

In [ ]:

```
def train_test_split(X, y, random_state=41, test_size=0.2):
    """
    Splits the data into training and testing sets.

    Parameters:
        X (numpy.ndarray): Features array of shape (n_samples, n_features).
        y (numpy.ndarray): Target array of shape (n_samples,).
        random_state (int): Seed for the random number generator. Default is 42.
        test_size (float): Proportion of samples to include in the test set. Default is 0.2.

    Returns:
        Tuple[numpy.ndarray]: A tuple containing X_train, X_test, y_train, y_test.
    """
    # Get number of samples
    n_samples = X.shape[0]

    # Set the seed for the random number generator
    np.random.seed(random_state)

    # Shuffle the indices
    shuffled_indices = np.random.permutation(np.arange(n_samples))

    # Determine the size of the test set
    test_size = int(n_samples * test_size)

    # Split the indices into test and train
    test_indices = shuffled_indices[:test_size]
    train_indices = shuffled_indices[test_size:]

    # Split the features and target arrays into test and train
    X_train, X_test = X[train_indices], X[test_indices]
    y_train, y_test = y[train_indices], y[test_indices]

    return X_train, X_test, y_train, y_test
```

In [ ]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state=42) #split the  data into traing an
```

In [ ]:

```
class SVM:


    def __init__(self, iterations=1000, lr=0.01, lambdaa=0.01):

        self.lambdaa = lambdaa
        self.iterations = iterations
        self.lr = lr
        self.w = None
        self.b = None
    def initialize_parameters(self, X):

        m, n = X.shape
        self.w = np.zeros(n)
        self.b = 0

    def gradient_descent(self, X, y):

        y_ = np.where(y <= 0, -1, 1)
        for i, x in enumerate(X):
            if y_[i] * (np.dot(x, self.w) - self.b) >= 1:
                dw = 2 * self.lambdaa * self.w
                db = 0
            else:
                dw = 2 * self.lambdaa * self.w - np.dot(x, y_[i])
                db = y_[i]
            self.update_parameters(dw, db)

    def update_parameters(self, dw, db):

        self.w = self.w - self.lr * dw
        self.b = self.b - self.lr * db
    def fit(self, X, y):

        self.initialize_parameters(X)
        for i in range(self.iterations):
            self.gradient_descent(X, y)


    def predict(self, X):

        # get the outputs
        output = np.dot(X, self.w) - self.b
        # get the signs of the labels depending on if it's greater/less than zero
        label_signs = np.sign(output)
        #set predictions to 0 if they are less than or equal to -1 else set them to 1
        predictions = np.where(label_signs <= -1, 0, 1)
        return predictions
```

In [ ]:

```
def accuracy(y_true, y_pred):

    total_samples = len(y_true)
    correct_predictions = np.sum(y_true == y_pred)
    return (correct_predictions / total_samples)
```

Output

In [ ]:

```
model = SVM()
model.fit(X_train,y_train)
predictions = model.predict(X_test)

accuracy(y_test, predictions)
```

Out[ ]:

```
0.9823008849557522
```

PROGRAM 8

Date: 31-05-2024

Build Artificial Neural Network model with back propagation on a given dataset

Algorithm

31/5/24

Date __/__/__
Page ____

Lab - 10

Build ANN with Back propogation

Algorithm :-

① Create feed forward network with n inputs, n hidden units, n out outputs.

② Initialize all network weights to small random numbers.

③ Until the termination condition is met :-
DO

* For each $(\vec{x}, \vec{t})$ in training examples:
  - → Propogate input forward.
  - → Propogate errors Backward
  - → For each hidden unit h, calculate error.
  - → update weight.

Output :-

The ~~testing~~ accuracy measured was 7/9.

Code

In [1]:
```
import numpy as np
from sklearn.model_selection import train_test_split

db = np.loadtxt("/content/duke-breast-cancer.txt")
print("Database raw shape (%s,%s)" % np.shape(db))
```

```
Database raw shape (86,7130)
```

In [2]:
```
np.random.shuffle(db)
y = db[:, 0]
x = np.delete(db, [0], axis=1)
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.1)
print(np.shape(x_train),np.shape(x_test))
```

```
(77, 7129) (9, 7129)
```

In [3]:
```
hidden_layer = np.zeros(72)
weights = np.random.random((len(x[0]), 72))
output_layer = np.zeros(2)
hidden_weights = np.random.random((72, 2))
```

In [4]:
```
def sum_function(weights, index_locked_col, x):
    result = 0
    for i in range(0, len(x)):
        result += x[i] * weights[i][index_locked_col]
    return result
```

In [5]:
```
def activate_layer(layer, weights, x):
    for i in range(0, len(layer)):
        layer[i] = 1.7159 * np.tanh(2.0 * sum_function(weights, i, x) / 3.0)
```

In [6]:
```
def soft_max(layer):
    soft_max_output_layer = np.zeros(len(layer))
    for i in range(0, len(layer)):
        denominator = 0
        for j in range(0, len(layer)):
            denominator += np.exp(layer[j] - np.max(layer))
        soft_max_output_layer[i] = np.exp(layer[i] - np.max(layer)) / denominator
    return soft_max_output_layer
```

In [7]:
```
def recalculate_weights(learning_rate, weights, gradient, activation):
    for i in range(0, len(weights)):
        for j in range(0, len(weights[i])):
            weights[i][j] = (learning_rate * gradient[j] * activation[i]) + weights[i][j]
```

In [8]:
```
def back_propagation(hidden_layer, output_layer, one_hot_encoding, learning_rate, x):
    output_derivative = np.zeros(2)
    output_gradient = np.zeros(2)
    for i in range(0, len(output_layer)):
        output_derivative[i] = (1.0 - output_layer[i]) * output_layer[i]
    for i in range(0, len(output_layer)):
        output_gradient[i] = output_derivative[i] * (one_hot_encoding[i] - output_layer[i])
    hidden_derivative = np.zeros(72)
    hidden_gradient = np.zeros(72)
    for i in range(0, len(hidden_layer)):
        hidden_derivative[i] = (1.0 - hidden_layer[i]) * (1.0 + hidden_layer[i])
    for i in range(0, len(hidden_layer)):
        sum_ = 0
        for j in range(0, len(output_gradient)):
            sum_ += output_gradient[j] * hidden_weights[i][j]
        hidden_gradient[i] = sum_ * hidden_derivative[i]
    recalculate_weights(learning_rate, hidden_weights, output_gradient, hidden_layer)
    recalculate_weights(learning_rate, weights, hidden_gradient, x)
```

Output

In [9]:

```
one_hot_encoding = np.zeros((2,2))
for i in range(0, len(one_hot_encoding)):
    one_hot_encoding[i][i] = 1
training_correct_answers = 0
for i in range(0, len(x_train)):
    activate_layer(hidden_layer, weights, x_train[i])
    activate_layer(output_layer, hidden_weights, hidden_layer)
    output_layer = soft_max(output_layer)
    training_correct_answers += 1 if y_train[i] == np.argmax(output_layer) else 0
    back_propagation(hidden_layer, output_layer, one_hot_encoding[int(y_train[i])], -1, x_train[i])
print("MLP Correct answers while learning: %s / %s (Accuracy = %s) on %s database." % (training_correct_answers, len(x_trai
                                                                                      training_correct_answers/len(x_train
```

```
MLP Correct answers while learning: 51 / 77 (Accuracy = 0.6623376623376623) on Duke breast cancer database.
```

In [10]:

```
testing_correct_answers = 0
for i in range(0, len(x_test)):
    activate_layer(hidden_layer, weights, x_test[i])
    activate_layer(output_layer, hidden_weights, hidden_layer)
    output_layer = soft_max(output_layer)
    testing_correct_answers += 1 if y_test[i] == np.argmax(output_layer) else 0
print("MLP Correct answers while testing: %s / %s (Accuracy = %s) on %s database" % (testing_correct_answers, len(x_test),
                                                                                    testing_correct_answers/len(x_test), "I
```

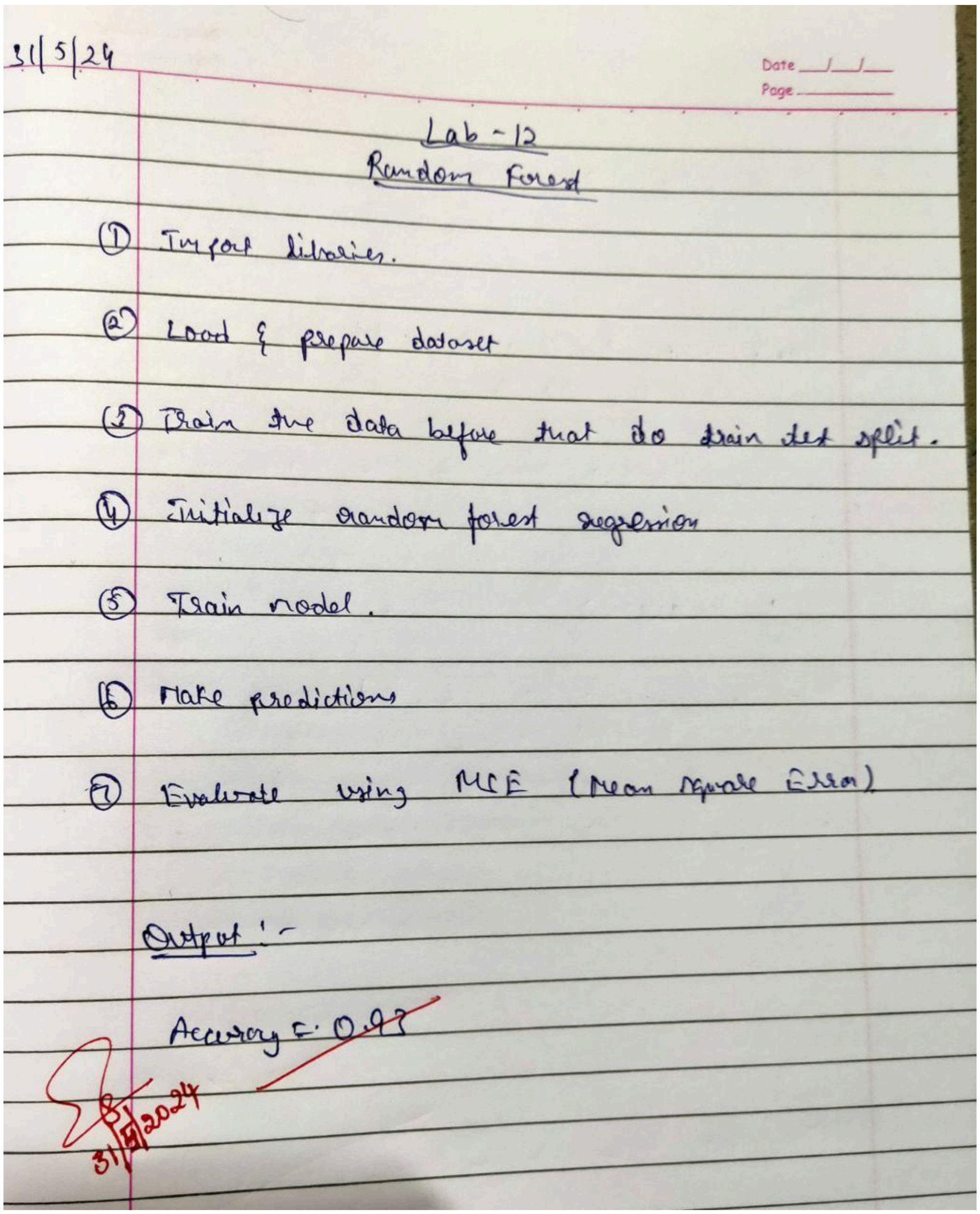
```
MLP Correct answers while testing: 9 / 9 (Accuracy = 1.0) on Duke breast cancer database
```

PROGRAM 9

Date: 31-05-2024

a) Implement Random forest ensemble method on a given dataset.

Algorithm



31/5/24

Date __/__/__
Page ______

Lab - 12

Random Forest

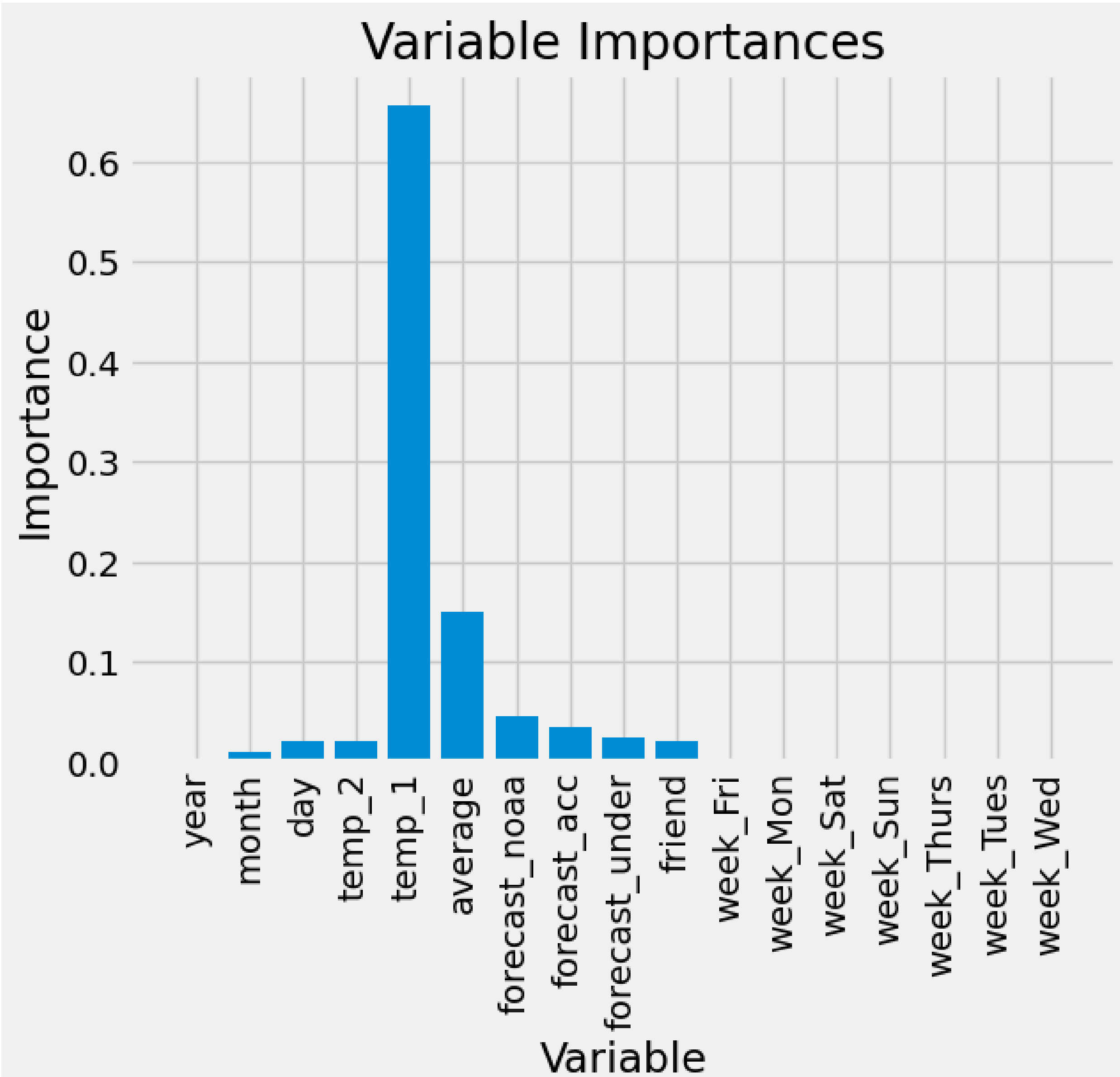
1. Import libraries.
2. Load & prepare dataset
3. Train the data before that do train test split.
4. Initialize random forest regression
5. Train model.
6. Make predictions
7. Evaluate using MSE (Mean Square Error)

Output :-

Accuracy = 0.93

31/5/2024

Output



Variable Importances
Importance
0.0
0.1
0.2
0.3
0.4
0.5
0.6
year
month
day
temp_2
temp_1
average
forecast_noaa
forecast_acc
forecast_under
friend
week_Fri
week_Mon
week_Sat
week_Sun
week_Thurs
week_Tues
week_Wed
Variable

b) Implement Boosting ensemble method on a given dataset.

Algorithm

31/5/24

Date / /
Page

Lab - 11
AdaBoost Algorithm

① Import libraries.

② Load and prepare data.

③ Initialize adaboost model - (learning rate, DesFunction)

④ Make the model train.

⑤ Make predictions.

⑥ Evaluate model on metrics like MAE.

Output :-

Accuracy :- 0.94.

Code

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
sns.set_style("whitegrid")
plt.style.use("fivethirtyeight")
```

In [2]:
```
df = pd.read_csv("/content/diabetes.csv")
df.head()
```

Out[2]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	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

In [3]:
```
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
```

In [4]:
```
df.isnull().sum()
```

Out[4]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

In [5]:
```
pd.set_option('display.float_format', '{:.2f}'.format)
df.describe()
```

Out[5]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
count	768.00	768.00	768.00	768.00	768.00	768.00	768.00	768.00	768.00
mean	3.85	120.89	69.11	20.54	79.80	31.99	0.47	33.24	0.35
std	3.37	31.97	19.36	15.95	115.24	7.88	0.33	11.76	0.48
min	0.00	0.00	0.00	0.00	0.00	0.00	0.08	21.00	0.00
25%	1.00	99.00	62.00	0.00	0.00	27.30	0.24	24.00	0.00
50%	3.00	117.00	72.00	23.00	30.50	32.00	0.37	29.00	0.00
75%	6.00	140.25	80.00	32.00	127.25	36.60	0.63	41.00	1.00
max	17.00	199.00	122.00	99.00	846.00	67.10	2.42	81.00	1.00

In [6]:

```
categorical_val = []
continous_val = []
for column in df.columns:
#     print('==============================')
#     print(f"{column} : {df[column].unique()}")
    if len(df[column].unique()) <= 10:
        categorical_val.append(column)
    else:
        continous_val.append(column)
```

In [7]:

```
df.columns
```

Out[7]:

```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

In [8]:

```
# How many missing zeros are mising in each feature
feature_columns = [
    'Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness',
    'Insulin', 'BMI', 'DiabetesPedigreeFunction', 'Age'
]

for column in feature_columns:
    print("============================================")
    print(f"{column} ==> Missing zeros : {len(df.loc[df[column] == 0])}")
```

```
============================================
Pregnancies ==> Missing zeros : 111
============================================
Glucose ==> Missing zeros : 5
============================================
BloodPressure ==> Missing zeros : 35
============================================
SkinThickness ==> Missing zeros : 227
============================================
Insulin ==> Missing zeros : 374
============================================
BMI ==> Missing zeros : 11
============================================
DiabetesPedigreeFunction ==> Missing zeros : 0
============================================
Age ==> Missing zeros : 0
```

In [9]:

```
from sklearn.impute import SimpleImputer


fill_values = SimpleImputer(missing_values=0, strategy="mean", copy=False)
df[feature_columns] = fill_values.fit_transform(df[feature_columns])

for column in feature_columns:
    print("============================================")
    print(f"{column} ==> Missing zeros : {len(df.loc[df[column] == 0])}")
```

```
============================================
Pregnancies ==> Missing zeros : 0
============================================
Glucose ==> Missing zeros : 0
============================================
BloodPressure ==> Missing zeros : 0
============================================
SkinThickness ==> Missing zeros : 0
============================================
Insulin ==> Missing zeros : 0
============================================
BMI ==> Missing zeros : 0
============================================
DiabetesPedigreeFunction ==> Missing zeros : 0
============================================
Age ==> Missing zeros : 0
```

In [10]:
```
from sklearn.model_selection import train_test_split

X = df[feature_columns]
y = df.Outcome

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

In [11]:
```
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report


def evaluate(model, X_train, X_test, y_train, y_test):
    y_test_pred = model.predict(X_test)
    y_train_pred = model.predict(X_train)

    print("TRAINIG RESULTS: \n===============================")
    clf_report = pd.DataFrame(classification_report(y_train, y_train_pred, output_dict=True))
    print(f"CONFUSION MATRIX:\n{confusion_matrix(y_train, y_train_pred)}")
    print(f"ACCURACY SCORE:\n{accuracy_score(y_train, y_train_pred):.4f}")
    print(f"CLASSIFICATION REPORT:\n{clf_report}")

    print("TESTING RESULTS: \n===============================")
    clf_report = pd.DataFrame(classification_report(y_test, y_test_pred, output_dict=True))
    print(f"CONFUSION MATRIX:\n{confusion_matrix(y_test, y_test_pred)}")
    print(f"ACCURACY SCORE:\n{accuracy_score(y_test, y_test_pred):.4f}")
    print(f"CLASSIFICATION REPORT:\n{clf_report}")
```

In [12]:
```
from sklearn.ensemble import AdaBoostClassifier

ada_boost_clf = AdaBoostClassifier(n_estimators=30)
ada_boost_clf.fit(X_train, y_train)
evaluate(ada_boost_clf, X_train, X_test, y_train, y_test)
```

Output-AdaBoost

```
TRAINIG RESULTS:
===============================
CONFUSION MATRIX:
[[310  39]
 [ 51 137]]
ACCURACY SCORE:
0.8324
CLASSIFICATION REPORT:
                0      1  accuracy  macro avg  weighted avg
precision    0.86   0.78      0.83       0.82          0.83
recall       0.89   0.73      0.83       0.81          0.83
f1-score     0.87   0.75      0.83       0.81          0.83
support    349.00 188.00      0.83     537.00        537.00
TESTING RESULTS:
===============================
CONFUSION MATRIX:
[[123  28]
 [ 27  53]]
ACCURACY SCORE:
0.7619
CLASSIFICATION REPORT:
                0     1  accuracy  macro avg  weighted avg
precision    0.82  0.65      0.76       0.74          0.76
recall       0.81  0.66      0.76       0.74          0.76
f1-score     0.82  0.66      0.76       0.74          0.76
support    151.00 80.00      0.76     231.00        231.00
```

Output- GradientBoost

```
TRAINIG RESULTS:
===============================
CONFUSION MATRIX:
[[342   7]
 [ 19 169]]
ACCURACY SCORE:
0.9516
CLASSIFICATION REPORT:
                0      1  accuracy  macro avg  weighted avg
precision    0.95   0.96      0.95       0.95          0.95
recall       0.98   0.90      0.95       0.94          0.95
f1-score     0.96   0.93      0.95       0.95          0.95
support    349.00 188.00      0.95     537.00        537.00
TESTING RESULTS:
===============================
CONFUSION MATRIX:
[[116  35]
 [ 26  54]]
ACCURACY SCORE:
0.7359
CLASSIFICATION REPORT:
                0     1  accuracy  macro avg  weighted avg
precision    0.82  0.61      0.74       0.71          0.74
recall       0.77  0.68      0.74       0.72          0.74
f1-score     0.79  0.64      0.74       0.72          0.74
support    151.00 80.00      0.74     231.00        231.00
```

PROGRAM 10

Date: 24-05-2024

Build k-Means algorithm to cluster a set of data stored in a .CSV file.

Algorithm

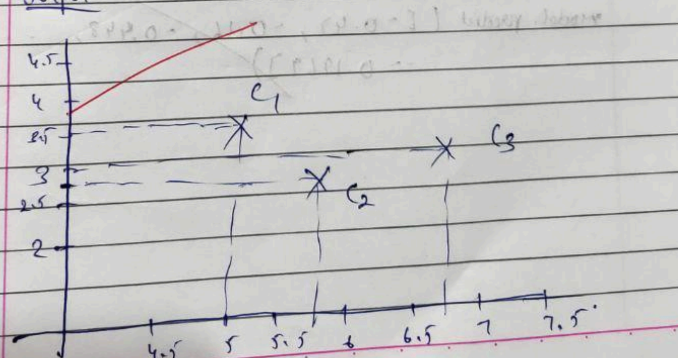
24/5/24

Lab-8

Kmeans Clustering Algorithm

1. Select the number K to decide the number of clusters.
2. Select random K points / centroids.
3. Assign each point to the closest centroid, which will form the predefined K cluster.
4. Calculate the variance & place a new centroid of each cluster.
5. Repeat 3 step, ~~reassign~~ update the centroids.
6. If any reassignment occurs go to step 4 else go to finish.
7. The model is ready.

Output



Code

Importing and initializing the data points

In [5]:
```
import matplotlib.pyplot as plt
import numpy as np
from sklearn.cluster import KMeans
```

In [6]:
```
from sklearn.datasets import make_blobs
X, y_true = make_blobs(n_samples=550, centers=4, cluster_std=0.60, random_state=0)
```

In [7]:
```
import plotly.express as px
fig = px.scatter(x =X[:, 0], y =X[:, 1],width=800,height=500)
fig.show()
```

Elbow Method to find optimal K

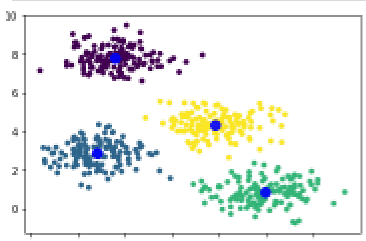
In [8]:
```
cost =[]
for i in range(1, 11):
        KM = KMeans(n_clusters = i, max_iter = 500)
        KM.fit(X)

        cost.append(KM.inertia_)

# plot the cost against K values
fig = px.line(x=range(1, 11), y=cost, width=600, height=400)
fig.show()
# the point of the elbow is the
# most optimal value for choosing k
```

Defining Model and fitting the same

In [9]:
```
kmeans = KMeans(n_clusters=4)
kmeans.fit(X)
y_kmeans = kmeans.predict(X)
```

In [10]:
```
fig = px.scatter(x =X[:, 0], y = X[:, 1], color=y_kmeans, width=700,height=400)
trace = px.scatter(x =X[:, 0], y = X[:, 1],  width=700,height=400)
fig.show()
```

In [11]:
```
plt.scatter(X[:, 0], X[:, 1], c=y_kmeans, s=20)
centers = kmeans.cluster_centers_
plt.scatter(centers[:, 0], centers[:, 1], c='blue', s=100, alpha=0.9);
plt.show()
```



Iris Dataset

In [12]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import datasets
```

In [24]:

```
iris = datasets.load_iris()
df = pd.DataFrame(iris.data)
df['class']=iris.target
df.columns=['sepal_len', 'sepal_wid', 'petal_len', 'petal_wid', 'class']
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   sepal_len  150 non-null    float64
 1   sepal_wid  150 non-null    float64
 2   petal_len  150 non-null    float64
 3   petal_wid  150 non-null    float64
 4   class      150 non-null    int64
dtypes: float64(4), int64(1)
memory usage: 6.0 KB
```

In [52]:

```
px.histogram(df, x ='class', color='class')
```

In [56]:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X = df.iloc[:,0:4].values
```

In [63]:

```
scaled_x = scaler.fit_transform(X)
```

In [74]:

```
model = KMeans(n_clusters=3,init='k-means++',random_state=0)
labels = model.fit_predict(scaled_x)
```

In [81]:

```
import plotly.graph_objects as go
fig = go.Figure()

 # Add trace
fig.add_trace(go.Histogram(x=labels,name="Predicted Labels"))
fig.add_trace(go.Histogram(x=df['class'],name="True Labels"))

# Overlay both histograms
fig.update_layout(barmode='overlay')
# Reduce opacity to see both histograms
fig.update_traces(opacity=0.75)
fig.show()
```

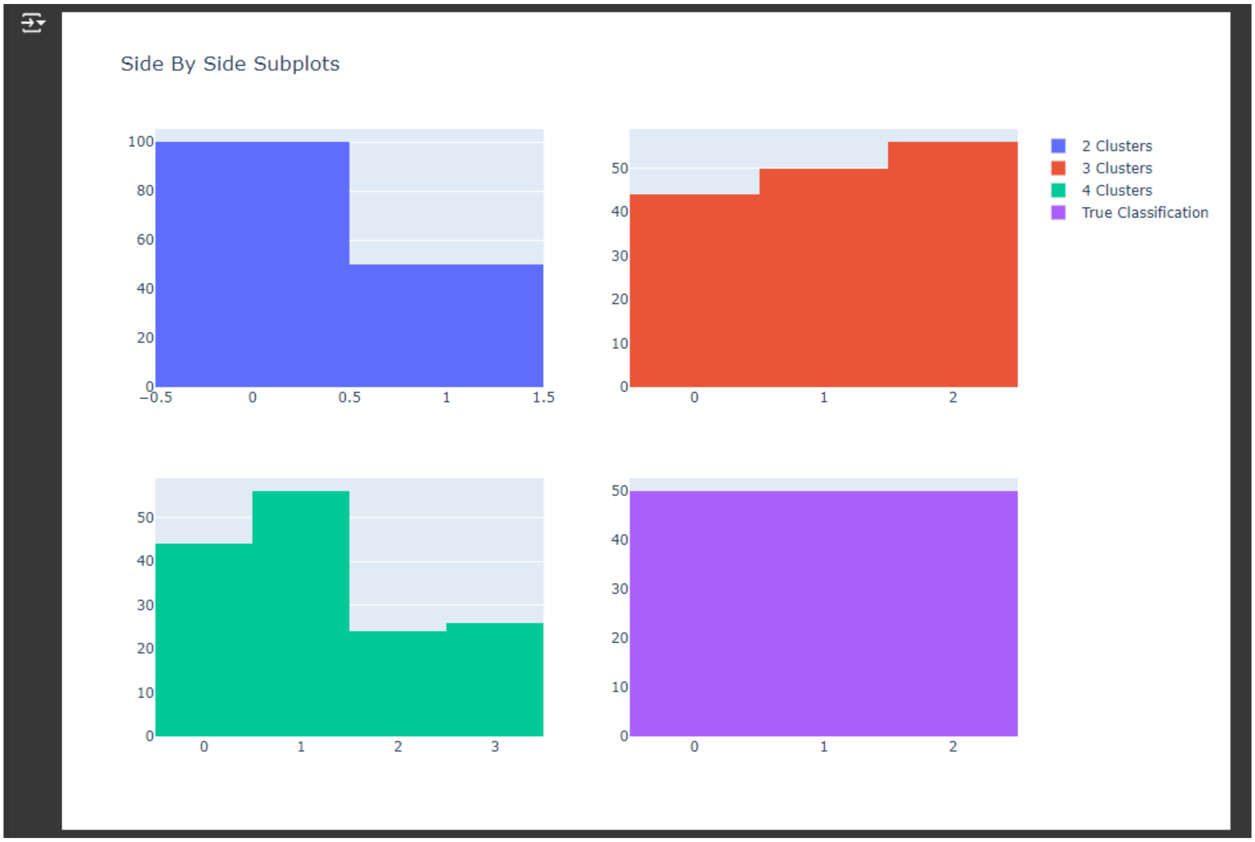
In [89]:

```
labels =[]
for i in range(2, 5):
        model = KMeans(n_clusters = i, max_iter = 500)
        model.fit(scaled_x)
        labels.append(model.fit_predict(scaled_x))
```

In [97]:

```
from plotly.subplots import make_subplots
import plotly.graph_objects as go
fig = make_subplots(rows=2, cols=2)
for i in range(0, 3):
    fig.add_trace(go.Histogram(x=labels[i],name="{} Clusters".format(i+2)),
             row=(i//2 + 1), col=(i%2 + 1))
fig.add_trace(go.Histogram(x=df['class'],name="True Classification"),
             row=(2), col=(2))
fig.update_layout(height=700, width=1000, title_text="Side By Side Subplots")

fig.show()
```

Output


Side By Side Subplots
2 Clusters
3 Clusters
4 Clusters
True Classification
100
80
60
40
20
0
−0.5
0
0.5
1
1.5
50
40
30
20
10
0
0
1
2
3