VISVESVARAYA TECHNOLOGICAL UNIVERSITY

“JnanaSangama”, Belgaum -590014, Karnataka.

LAB REPORT
On

MACHINE LEARNING

Submitted by

JEEVANTHI KASHYAP (1BM21CS080)

in partial fulfillment for the award of the degree of
BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING

B.M.S. COLLEGE OF ENGINEERING
(Autonomous Institution under VTU) BENGALURU-560019
March 2024 to June 2024

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 **JEEVANTHI KASHYAP(1BM21CS080)**, 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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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

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

Observation Screenshot:

5-04-24

Date
Page

Week-01 :-

① Write a python program to import and export data using Pandas library functions

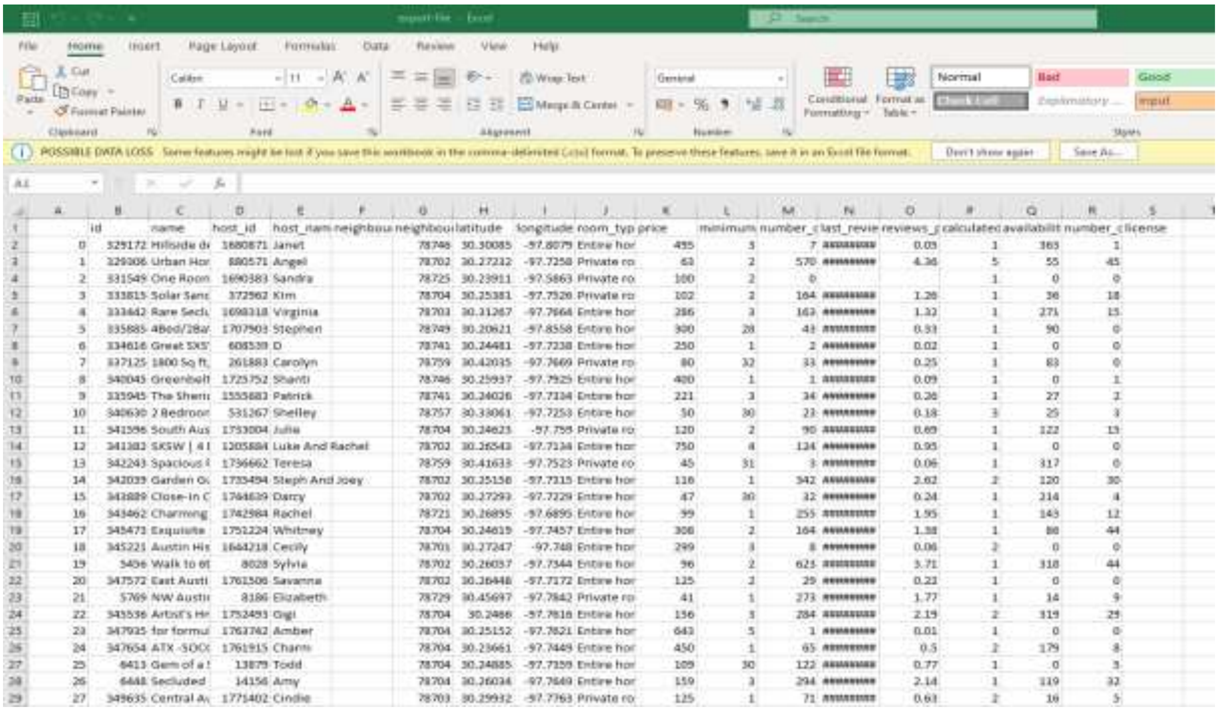
```
import pandas as pd
# Read csv file
airbnd_data = pd.read_csv("listings.csv")
# View first 5 rows
airbnd_data.head()

airbndb_data.to_csv("export-file.csv")
```

Code and Output:

```
import pandas as pd
# Read the CSV file
airbnb_data = pd.read_csv("listings.csv")
# View the first 5 rows
airbnb_data.head()
```

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_reviews	last_r
0	329172	Hillside designer home,10 min.dwntn	1680871	Janet	NaN	78746	30.30085	-97.80794	Entire home/apt	495	3	7	2022-
1	329306	Urban Homestead, 5 minutes to downtown	880571	Angel	NaN	78702	30.27232	-97.72579	Private room	63	2	570	2022-
2	331549	One Room with Private Bathroom	1690383	Sandra	NaN	78725	30.23911	-97.58625	Private room	100	2	0	
3	333815	Solar Sanctuary - Austin Room	372962	Kim	NaN	78704	30.25381	-97.75262	Private room	102	2	164	2022-
4	333442	Rare Secluded 1940s Estate	1698318	Virginia	NaN	78703	30.31267	-97.76641	Entire home/apt	286	3	163	2022-

```python
airbnb_data.to_csv("export-file.csv")
```



POSSIBLE DATA LOSS Some features might be lost if you save this workbook in the comma-delimited (.csv) format. To preserve these features, save it in an Excel file format.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1		id	name	host_id	host_nam	neighbou	neighbou	latitude	longitude	room_typ	price	minimum	number_c	last_revie	reviews_p	calculated	availabilit	number_c	license
2	0	329172	Hillside dr	1680871	Janet		78746	30.30085	-97.8079	Entire hor	495	3	7	########	0.09	1	365	1	
3	1	329306	Urban Hor	880571	Angel		78702	30.27232	-97.7258	Private ro	63	2	570	########	4.36	5	55	45	
4	2	331549	One Roon	1690383	Sandra		78725	30.23911	-97.5863	Private ro	100	2	0			1	0	0	
5	3	333815	Solar Sanc	372962	Kim		78704	30.25381	-97.7526	Private ro	102	2	164	########	1.26	1	36	18	
6	4	333442	Rare Seclu	1698318	Virginia		78703	30.31267	-97.7664	Entire hor	286	3	163	########	1.32	1	271	15	
7	5	335885	4Bed/2Ba	1707903	Stephen		78749	30.20621	-97.8558	Entire hor	300	28	43	########	0.33	1	90	0	
8	6	334616	Great SXS	608539	D		78741	30.24481	-97.7238	Entire hor	250	1	2	########	0.02	1	0	0	
9	7	337125	1800 Sq ft,	261883	Carolyn		78759	30.42035	-97.7669	Private ro	80	32	33	########	0.25	1	83	0	
10	8	340045	Greenbelt	1725752	Shanti		78746	30.25937	-97.7925	Entire hor	400	1	1	########	0.09	1	0	1	
11	9	335945	The Sheni	1555683	Patrick		78741	30.24026	-97.7134	Entire hor	221	3	34	########	0.26	1	27	2	
12	10	340630	2 Bedroor	531267	Shelley		78757	30.33061	-97.7253	Entire hor	50	30	23	########	0.18	3	25	3	
13	11	341596	South Aus	1753004	Julie		78704	30.24623	-97.759	Private ro	120	2	90	########	0.69	1	122	13	
14	12	341382	SXSW | 4 I	1205884	Luke And Rachel		78702	30.26543	-97.7134	Entire hor	750	4	124	########	0.95	1	0	0	
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16	14	342039	Garden O	1735494	Steph And Joey		78702	30.25158	-97.7315	Entire hor	116	1	342	########	2.62	2	120	30	
17	15	343889	Close-in C	1744639	Darcy		78702	30.27293	-97.7229	Entire hor	47	30	32	########	0.24	1	214	4	
18	16	343462	Charming	1742984	Rachel		78721	30.26895	-97.6895	Entire hor	99	1	255	########	1.95	1	143	12	
19	17	345473	Exquisite	1751224	Whitney		78704	30.24619	-97.7457	Entire hor	308	2	164	########	1.38	1	88	44	
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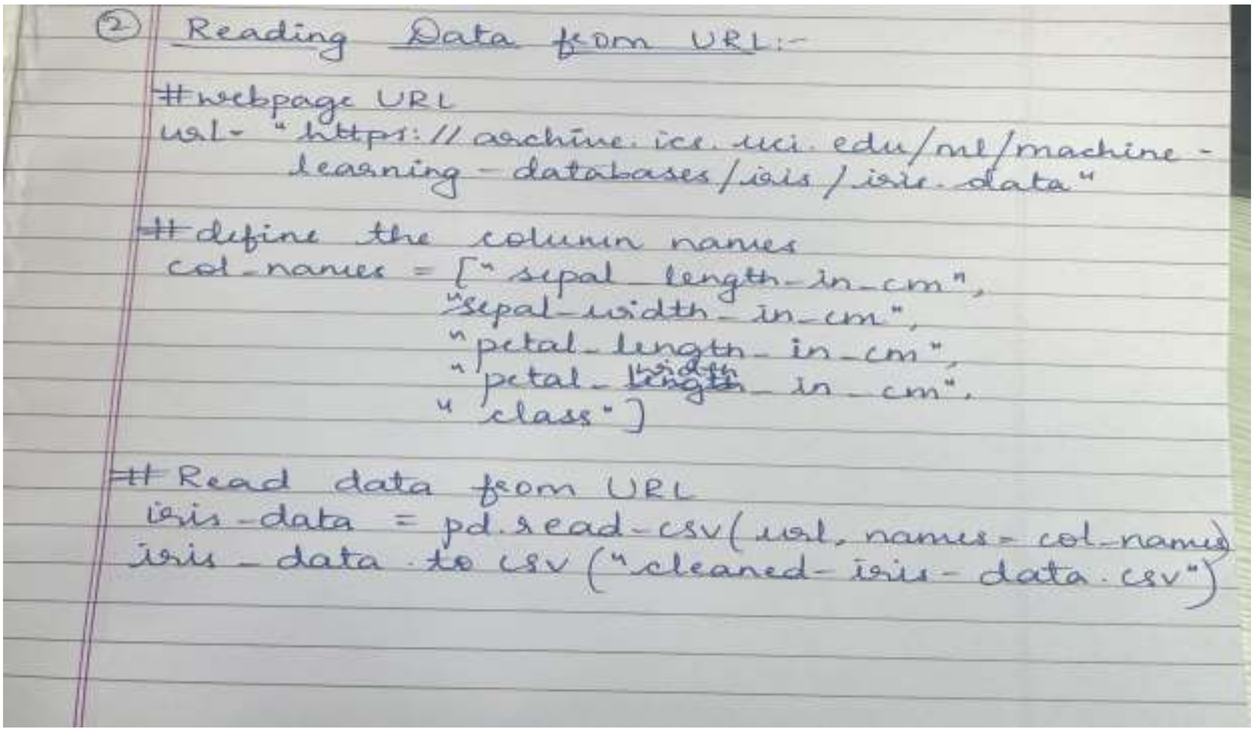
21	19	5456	Walk to 6t	8028	Sylvia		78702	30.26037	-97.7344	Entire hor	96	2	623	########	3.71	1	318	44	
22	20	347572	East Austi	1761506	Savanna		78702	30.26448	-97.7172	Entire hor	125	2	29	########	0.22	1	0	0	
23	21	5769	NW Austir	8186	Elizabeth		78729	30.45697	-97.7842	Private ro	41	1	273	########	1.77	1	14	9	
24	22	345536	Artist's Ho	1752493	Gigi		78704	30.2486	-97.7816	Entire hor	156	3	284	########	2.19	2	319	29	
25	23	347935	for formul	1763742	Amber		78704	30.25152	-97.7821	Entire hor	643	5	1	########	0.01	1	0	0	
26	24	347654	ATX -SOC(	1761915	Charm		78704	30.23661	-97.7449	Entire hor	450	1	65	########	0.5	2	179	8	
27	25	6413	Gem of a !	13879	Todd		78704	30.24885	-97.7359	Entire hor	109	30	122	########	0.77	1	0	3	
28	26	6448	Secluded	14156	Amy		78704	30.26034	-97.7649	Entire hor	159	3	294	########	2.14	1	119	32	
29	27	349635	Central Au	1771402	Cindie		78703	30.29932	-97.7763	Private ro	125	1	71	########	0.63	2	16	5	

Reading data from URL:

Observation screenshot:



② Reading Data from URL:-

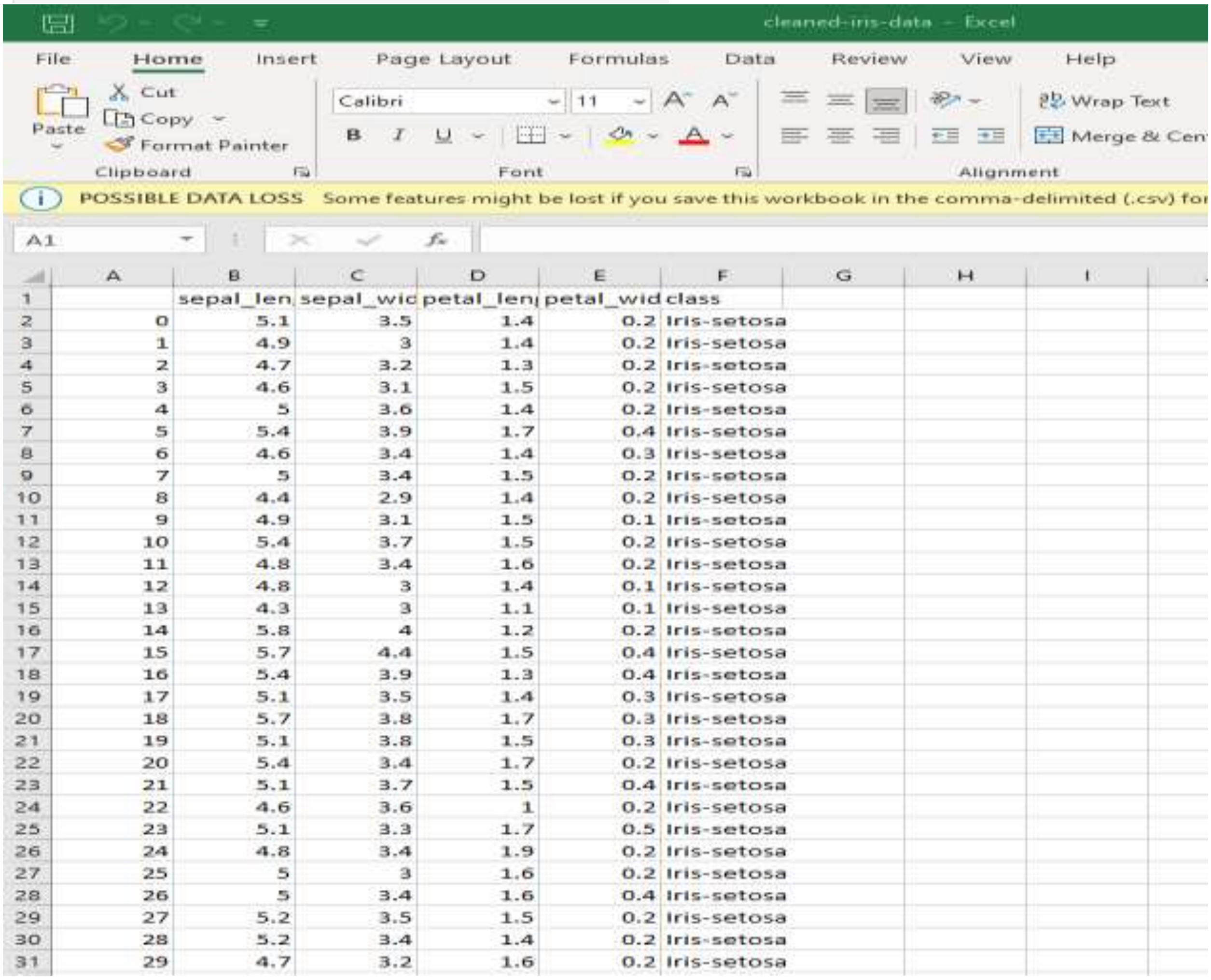
```
#webpage URL
url= "https://archive.ics.uci.edu/ml/machine-
     learning-databases/iris/iris.data"

#define the column names
col_names = ["sepal_length_in_cm",
             "sepal_width_in_cm",
             "petal_length_in_cm",
             "petal_width_in_cm",
             "class"]

#Read data from URL
iris_data = pd.read_csv(url, names=col_names)
iris_data.to_csv("cleaned-iris-data.csv")
```

Code and output:

```python
#Webpage URL
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data"

# Define the column names
col_names = ["sepal_length_in_cm",
             "sepal_width_in_cm",
             "petal_length_in_cm",
             "petal_width_in_cm",
             "class"]

# Read data from URL
iris_data = pd.read_csv(url, names=col_names)

iris_data.head()
```

	sepal_length_in_cm	sepal_width_in_cm	petal_length_in_cm	petal_width_in_cm	class
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

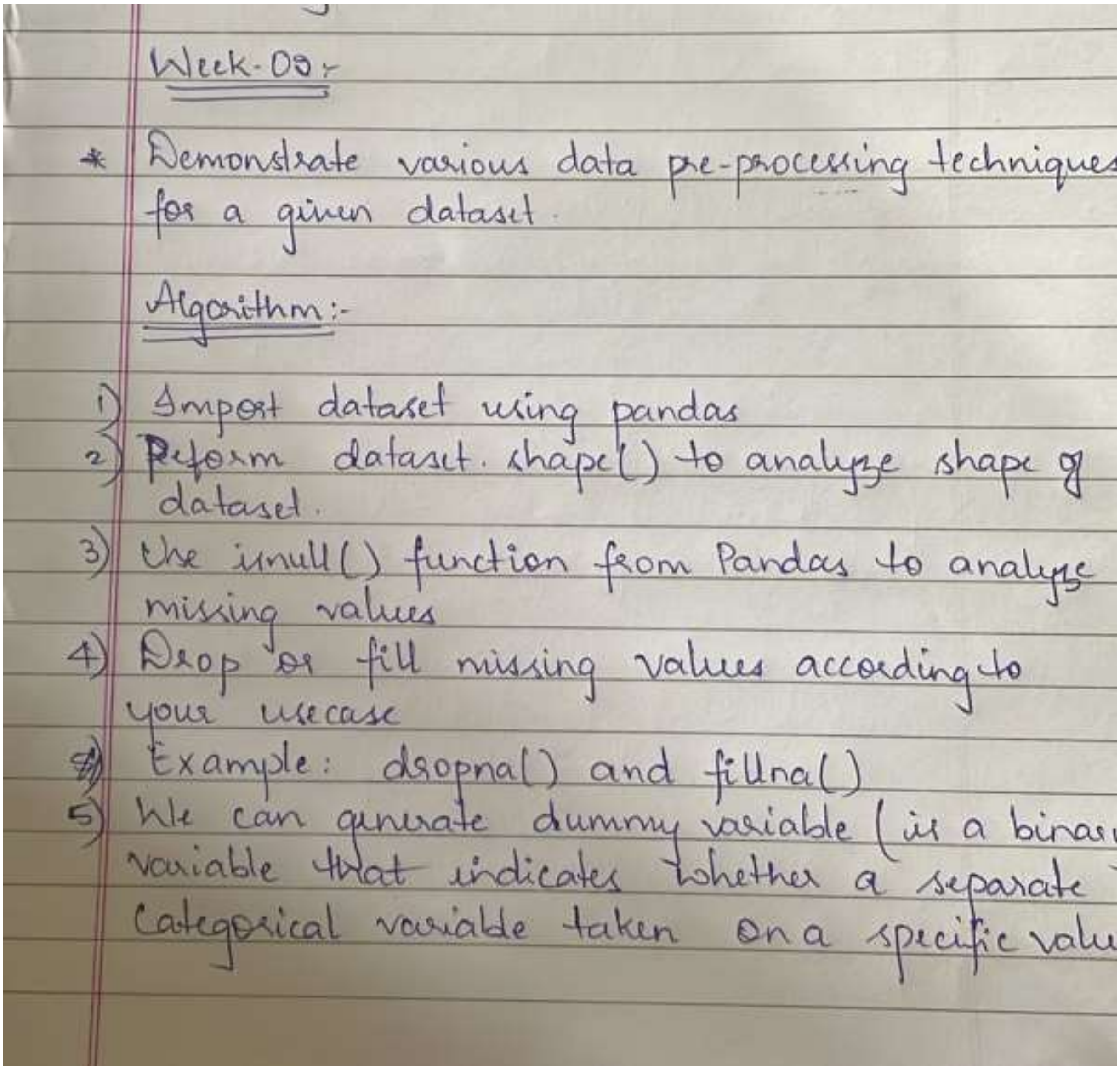
```python
iris_data.to_csv("cleaned-iris-data.csv")
```



	A	B	C	D	E	F
1		sepal_len	sepal_wid	petal_len	petal_wid	class
2	0	5.1	3.5	1.4	0.2	Iris-setosa
3	1	4.9	3	1.4	0.2	Iris-setosa
4	2	4.7	3.2	1.3	0.2	Iris-setosa
5	3	4.6	3.1	1.5	0.2	Iris-setosa
6	4	5	3.6	1.4	0.2	Iris-setosa
7	5	5.4	3.9	1.7	0.4	Iris-setosa
8	6	4.6	3.4	1.4	0.3	Iris-setosa
9	7	5	3.4	1.5	0.2	Iris-setosa
10	8	4.4	2.9	1.4	0.2	Iris-setosa
11	9	4.9	3.1	1.5	0.1	Iris-setosa
12	10	5.4	3.7	1.5	0.2	Iris-setosa
13	11	4.8	3.4	1.6	0.2	Iris-setosa
14	12	4.8	3	1.4	0.1	Iris-setosa
15	13	4.3	3	1.1	0.1	Iris-setosa
16	14	5.8	4	1.2	0.2	Iris-setosa
17	15	5.7	4.4	1.5	0.4	Iris-setosa
18	16	5.4	3.9	1.3	0.4	Iris-setosa
19	17	5.1	3.5	1.4	0.3	Iris-setosa
20	18	5.7	3.8	1.7	0.3	Iris-setosa
21	19	5.1	3.8	1.5	0.3	Iris-setosa
22	20	5.4	3.4	1.7	0.2	Iris-setosa
23	21	5.1	3.7	1.5	0.4	Iris-setosa
24	22	4.6	3.6	1	0.2	Iris-setosa
25	23	5.1	3.3	1.7	0.5	Iris-setosa
26	24	4.8	3.4	1.9	0.2	Iris-setosa
27	25	5	3	1.6	0.2	Iris-setosa
28	26	5	3.4	1.6	0.4	Iris-setosa
29	27	5.2	3.5	1.5	0.2	Iris-setosa
30	28	5.2	3.4	1.4	0.2	Iris-setosa
31	29	4.7	3.2	1.6	0.2	Iris-setosa

2. Demonstrate various data pre-processing techniques for a given dataset

Observation Screenshot:



Week-02:-

* Demonstrate various data pre-processing techniques for a given dataset.

Algorithm:-

1) Import dataset using pandas
2) Perform dataset.shape() to analyze shape of dataset.
3) Use isnull() function from Pandas to analyze missing values
4) Drop or fill missing values according to your usecase
Example: dropna() and fillna()
5) We can generate dummy variable (is a binary variable that indicates whether a separate categorical variable taken on a specific valu

Code and Output:

```python
%matplotlib inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
```

```python
dataset = pd.read_csv("Data.csv")
df = pd.DataFrame(dataset)
print(df.head())
```

```
   Country   Age   Salary Purchased
0   France  44.0  72000.0        No
1    Spain  27.0  48000.0       Yes
2  Germany  30.0  54000.0        No
3    Spain  38.0  61000.0        No
4  Germany  40.0      NaN       Yes
```

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

```python
print(X)
```

```
[['France' 44.0 72000.0]
 ['Spain' 27.0 48000.0]
 ['Germany' 30.0 54000.0]
 ['Spain' 38.0 61000.0]
 ['Germany' 40.0 nan]
 ['France' 35.0 58000.0]
 ['Spain' nan 52000.0]
 ['France' 48.0 79000.0]
 ['Germany' 50.0 83000.0]
 ['France' 37.0 67000.0]]
```

```python
print(y)
```

```
['No' 'Yes' 'No' 'No' 'Yes' 'Yes' 'No' 'Yes' 'No' 'Yes']
```

```
df2
```

	Country	Age	Salary	Purchased
0	France	44.0	72000.0	No
1	Spain	27.0	48000.0	Yes
2	Germany	30.0	54000.0	No
3	Spain	38.0	61000.0	No
4	Germany	40.0	NaN	Yes
5	France	35.0	58000.0	Yes
6	Spain	NaN	52000.0	No
7	France	48.0	79000.0	Yes
8	Germany	50.0	83000.0	No
9	France	37.0	67000.0	Yes

```
pd.get_dummies(df2)
```

	Age	Salary	Country_France	Country_Germany	Country_Spain	Purchased_No	Purchased_Yes
0	44.0	72000.0	True	False	False	True	False
1	27.0	48000.0	False	False	True	False	True
2	30.0	54000.0	False	True	False	True	False
3	38.0	61000.0	False	False	True	True	False
4	40.0	NaN	False	True	False	False	True
5	35.0	58000.0	True	False	False	False	True
6	NaN	52000.0	False	False	True	True	False
7	48.0	79000.0	True	False	False	False	True
8	50.0	83000.0	False	True	False	True	False
9	37.0	67000.0	True	False	False	False	True

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

Observation Screenshot:

12-04-24

Week-9: ID3

ID3 Algorithm:-

ID3 (Examples, Target-Attribute, Attributes)

{ Examples are the training examples
Target-Attribute - whose value is predicted by the tree.
Attributes - List of other attributes that may be tested by the learned decision tree

→ Create a Root node for the tree
→ If all examples are positive, Return the single-node tree root with label = +
→ If all examples are negative, Return the single-node tree Root, with label = -
→ If Attributes are empty, Return the single-node tree Root, with label = most common value of target-attribute in Examples
→ Otherwise Begin
→ A ← the attribute from attributes that best * classifies Examples
→ The decision attribute for Root ← A
→ for each possible value, Vi of A
→ Add a new tree branch below Root, corresponding to the test A = Vi
→ Let Examples Vi be the subset of Examples that have value Vi for A
→ If Examples Vi is empty
→ Then below this new branch add a

leaf node with label = most common value of target-attributes in Examples
→ Else below this new branch add the subtree
ID3(Examples$_{vi}$, Target-attribute, Attributes - {A})
→ End
→ Return Root.

* - best attribute - the one with highest information gain

Output :-

1) Entropy of data = 0.9331

2) Calculating Entropy and information gain for the following (based on dataset):

Pregnancies - Entropy - 3.482, IG: 0.062
Glucose - Entropy - 6.751, IG: 0.304
Blood Pressure: Entropy - 4.792, IG: 0.059
SkinThickness: Entropy - 4.586, IG: 0.082
Insulin: Entropy: 4.682, IG - 0.277
BMI: Entropy: 7.597 IG, IG - 0.344
DiabetesPedigreeFunction: Entropy: 8.829, IG: 0.651
Age: Entropy - 5.029, IG: 0.141

DiabetesPedigreeFunction <= 0.528
Entropy = 0.933
Samples = 768
value = [500, 268]
class = 0

Entropy = 0.87
samples = 509
value = [361, 148] class = 0

Entropy = 0.996
Samples = 259
value = [139, 120] class = ...

Code and Output:

```
import pandas as pd
from sklearn.tree import DecisionTreeClassifier, plot_tree
import matplotlib.pyplot as plt
import math
df = pd.read_csv('/content/diabetes.csv')
df.head()
```

	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

```
def calculate_entropy(data, target_column):
total_rows = len(data)
target_values = data[target_column].unique()

entropy = 0
for value in target_values:
        # Calculate the proportion of instances with the current value
        value_count = len(data[data[target_column] == value])
        proportion = value_count / total_rows
        entropy -= proportion * math.log2(proportion)

return entropy

entropy_outcome = calculate_entropy(df, 'Outcome')
print(f"Entropy of the dataset: {entropy_outcome}")
```

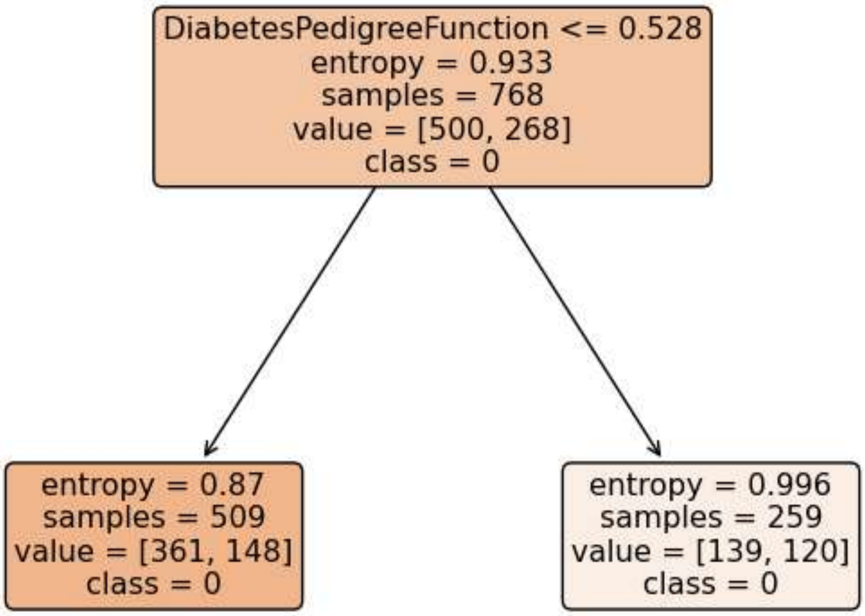
```
Entropy of the dataset: 0.9331343166407831
```

```
def calculate_entropy(data, target_column): # for each categorical variable
total_rows = len(data)
target_values = data[target_column].unique()

entropy = 0
for value in target_values:
        # Calculate the proportion of instances with the current value
        value_count = len(data[data[target_column] == value])
        proportion = value_count / total_rows
        entropy -= proportion * math.log2(proportion) if proportion != 0 else 0

return entropy

def calculate_information_gain(data, feature, target_column):
```

```
# Calculate weighted average entropy for the feature
unique_values = data[feature].unique()
weighted_entropy = 0

for value in unique_values:
        subset = data[data[feature] == value]
        proportion = len(subset) / len(data)
        weighted_entropy += proportion * calculate_entropy(subset, target_column)

# Calculate information gain
information_gain = entropy_outcome - weighted_entropy

return information_gain
for column in df.columns[:-1]:
entropy = calculate_entropy(df, column)
information_gain = calculate_information_gain(df, column, 'Outcome')
print(f"{column} - Entropy: {entropy:.3f}, Information Gain: {information_gain:.3f}")
```

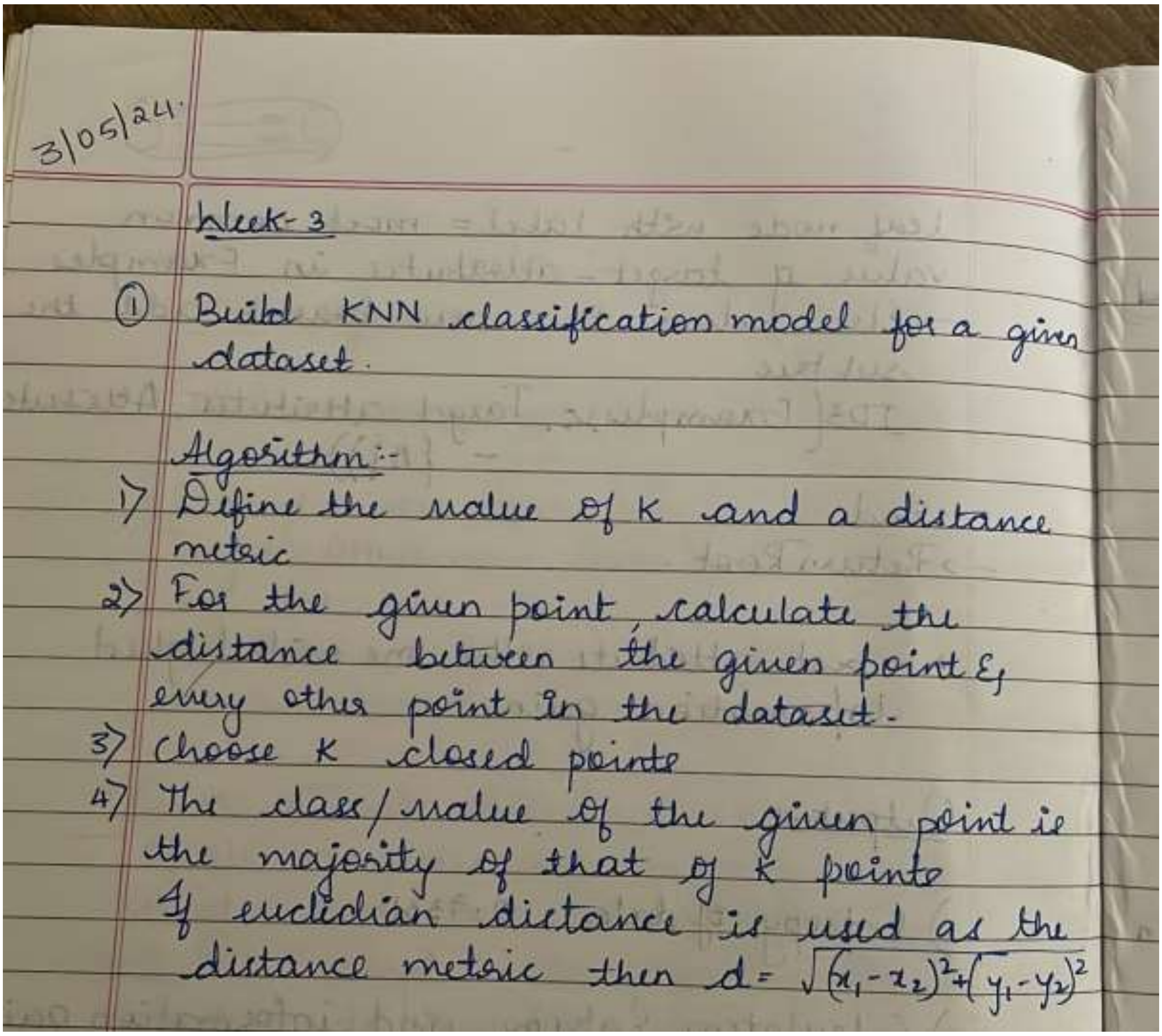
```
Pregnancies - Entropy: 3.482, Information Gain: 0.062
Glucose - Entropy: 6.751, Information Gain: 0.304
BloodPressure - Entropy: 4.792, Information Gain: 0.059
SkinThickness - Entropy: 4.586, Information Gain: 0.082
Insulin - Entropy: 4.682, Information Gain: 0.277
BMI - Entropy: 7.594, Information Gain: 0.344
DiabetesPedigreeFunction - Entropy: 8.829, Information Gain: 0.651
Age - Entropy: 5.029, Information Gain: 0.141
```

```
# Feature selection for the first step in making decision tree
selected_feature = 'DiabetesPedigreeFunction'

# Create a decision tree
clf = DecisionTreeClassifier(criterion='entropy', max_depth=1)
X = df[[selected_feature]]
y = df['Outcome']
clf.fit(X, y)

plt.figure(figsize=(8, 6))
plot_tree(clf, feature_names=[selected_feature], class_names=['0', '1'], filled=True,
rounded=True)
plt.show()
```


DiabetesPedigreeFunction <= 0.528
entropy = 0.933
samples = 768
value = [500, 268]
class = 0
entropy = 0.87
samples = 509
value = [361, 148]
class = 0
entropy = 0.996
samples = 259
value = [139, 120]
class = 0

4. Build KNN Classification model for a given dataset.

Observation Screenshot:



3/05/24.

Week - 3

① Build KNN classification model for a given dataset.

Algorithm :-

1> Define the value of K and a distance metric

2> For the given point, calculate the distance between the given point & every other point in the dataset.

3> Choose K closed points

4> The class / value of the given point is the majority of that of K points

If euclidian distance is used as the distance metric then $d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$

Code and output:

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

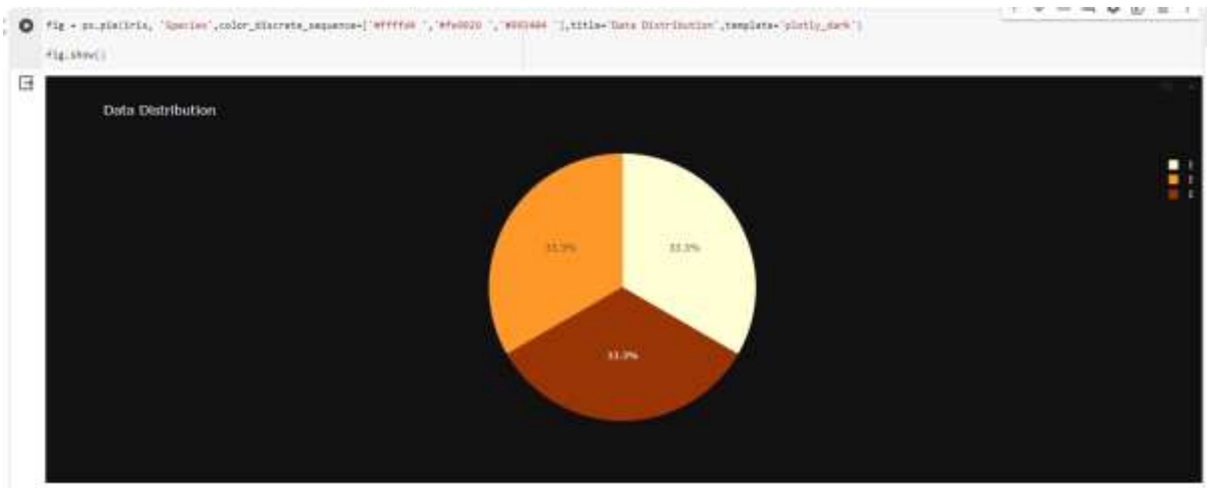
```
[3] iris = pd.read_csv("Iris.csv") #Load Data
    iris.drop('Id',inplace=True,axis=1) #Drop Id column
```

```
[4] iris.head()
```

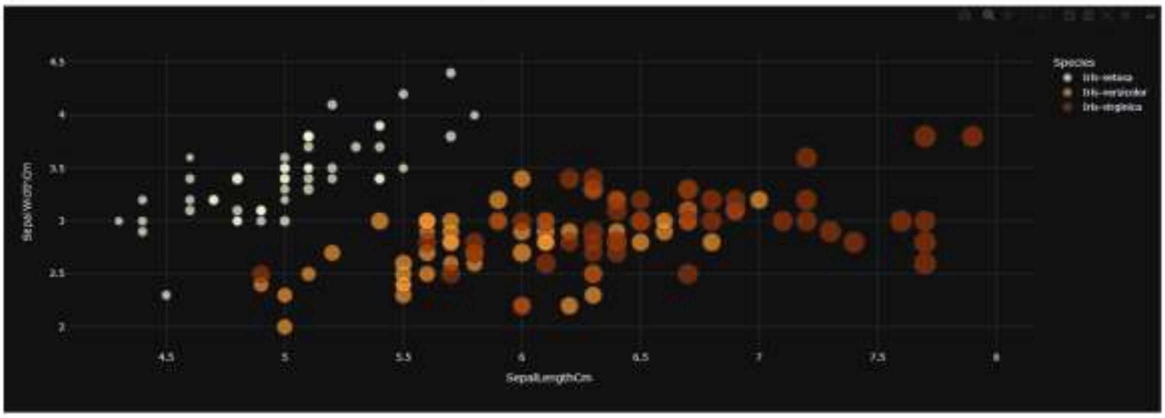
	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

Next steps: View recommended plots

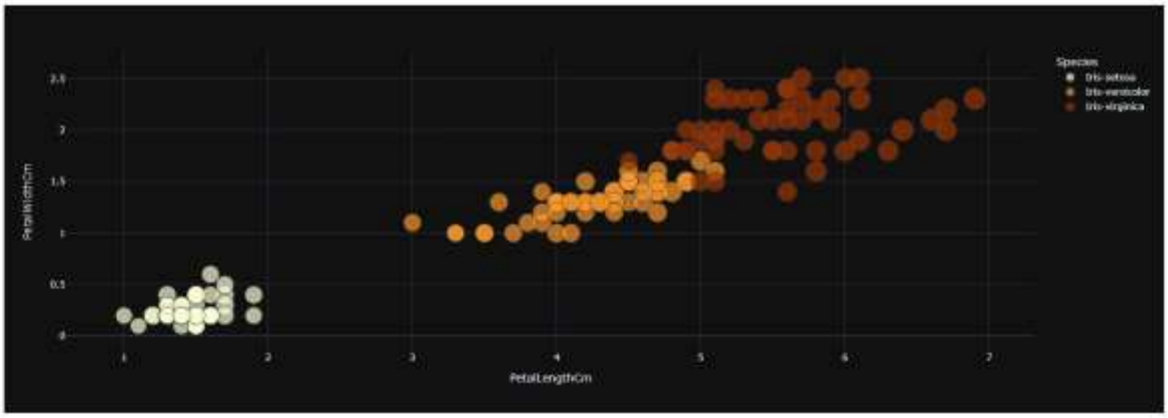
```
[5] X = iris.iloc[:,:-1] #Set our training data

    y = iris.iloc[:,-1] #Set training labels
```



```python
fig = px.scatter(data_frame=iris, x='SepalLengthCm',y='SepalWidthCm'
            ,color='Species',size='PetalLengthCm', color_discrete_sequence=['#ffffd4 ','#fe9929 ','#993404 '], template='plotly_dark',)

fig.show()
```




```python
fig = px.scatter(data_frame=iris, x='PetalLengthCm',y='PetalWidthCm'
            ,color='Species',size='SepalLengthCm', color_discrete_sequence=['#ffffd4 ','#fe9929 ','#993404 '], template='plotly_dark',)

fig.show()
```



```python
class KNN:
    """
    K-Nearest Neighbors (KNN) classification algorithm

    Parameters:
    -----------
    n_neighbors : int, optional (default=5)
        Number of neighbors to use in the majority vote.

    Methods:
    --------
    fit(X_train, y_train):
        Stores the values of X_train and y_train.

    predict(X):
        Predicts the class labels for each example in X.

    """
    def __init__(self, n_neighbors=5):
        self.n_neighbors = n_neighbors

    def euclidean_distance(self, x1, x2):
        """
        Calculate the Euclidean distance between two data points.

        Parameters:
        -----------
        x1 : numpy.ndarray, shape (n_features,)
            A data point in the dataset.

        x2 : numpy.ndarray, shape (n_features,)
            A data point in the dataset.

        Returns:
        --------
        distance : float
            The Euclidean distance between x1 and x2.
        """
        return np.linalg.norm(x1 - x2)
```

```python
def fit(self, X_train, y_train):
    """
    Stores the values of X_train and y_train.

    Parameters:
    -----------
    X_train : numpy.ndarray, shape (n_samples, n_features)
        The training dataset.

    y_train : numpy.ndarray, shape (n_samples,)
        The target labels.
    """
    self.X_train = X_train
    self.y_train = y_train

def predict(self, X):
    """
    Predicts the class labels for each example in X.

    Parameters:
    -----------
    X : numpy.ndarray, shape (n_samples, n_features)
        The test dataset.

    Returns:
    --------
    predictions : numpy.ndarray, shape (n_samples,)
        The predicted class labels for each example in X.
    """
    # Create empty array to store the predictions
    predictions = []
    # Loop over X examples
    for x in X:
        # Get prediction using the prediction helper function
        prediction = self._predict(x)
        # Append the prediction to the predictions list
        predictions.append(prediction)
    return np.array(predictions)
```

```python
def _predict(self, x):
    """
    Predicts the class label for a single example.

    Parameters:
    -----------
    x : numpy.ndarray, shape (n_features,)
        A data point in the test dataset.

    Returns:
    --------
    most_occuring_value : int
        The predicted class label for x.
    """
    # Create empty array to store distances
    distances = []
    # Loop over all training examples and compute the distance between x and all the training examples
    for x_train in self.X_train:
        distance = self.euclidean_distance(x, x_train)
        distances.append(distance)
    distances = np.array(distances)

    # Sort by ascendingly distance and return indices of the given n neighbours
    n_neighbors_idxs = np.argsort(distances)[: self.n_neighbors]

    # Get labels of n-neighbour indexes
    labels = self.y_train[n_neighbors_idxs]
    labels = list(labels)
    # Get the most frequent class in the array
    most_occuring_value = max(labels, key=labels.count)
    return most_occuring_value
```

```python
def train_test_split(X, y, random_state=42, 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
```

```python
[12] X_train, X_test, y_train, y_test = train_test_split(X.values, y.values, test_size = 0.2, random_state=42) #
```

```
[13] model = KNN(7)
     model.fit(X_train, y_train)
```

```
[14] def compute_accuracy(y_true, y_pred):
         """
         Computes the accuracy of a classification model.

         Parameters:
         y_true (numpy array): A numpy array of true labels for each data point.
         y_pred (numpy array): A numpy array of predicted labels for each data point.

         Returns:
         float: The accuracy of the model, expressed as a percentage.
         """
         y_true = y_true.flatten()
         total_samples = len(y_true)
         correct_predictions = np.sum(y_true == y_pred)
         return (correct_predictions / total_samples)
```

```
[15] predictions = model.predict(X_test)
     accuracy = compute_accuracy(y_test, predictions)
     print(f" our model got accuracy score of : {accuracy}")
```

```
 our model got accuracy score of : 0.9666666666666667
```

```
[16] from sklearn.neighbors import KNeighborsClassifier
     skmodel = KNeighborsClassifier(n_neighbors=7)
     skmodel.fit(X_train, y_train)
```

```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=7)
```

```
[17] sk_predictions = skmodel.predict(X_test)
     sk_accuracy = compute_accuracy(y_test, sk_predictions)
     print(f" sklearn-model got accuracy score of : {sk_accuracy}")
```

```
 sklearn-model got accuracy score of : 0.9666666666666667
```

5.Linear Regression
Observation Screenshot:

② Build Linear Regression model for a given set.

Algorithm :-

function linear_regression(x, y, learning_rate, num_iterations)
Initialize random values for slope(m) and intercept (b)
for i = 1 to num_iterations
# Step-2: Compute predictions
predictions = m * x + b.
# Step-3: Compute Error
errors = predictions - y

# Step-4: Compute loss function
loss = mean_squared_error(errors)
# Step-5: Gradient Descent
gradient_m = (2/N) * sum(errors * x)
gradient_m = (2/N) * sum(errors)
m = m - learning_rate * gradient_m
b = b - learning_rate * gradient_b.

Return m, b
function mean_squared_error(errors)
squared_errors = $errors^2$
mse = sum(squared_errors) / len(errors)
return mse.

Code and output:

```
import math
import numpy as np
import pandas as pd
import plotly.express as px
import pickle
```

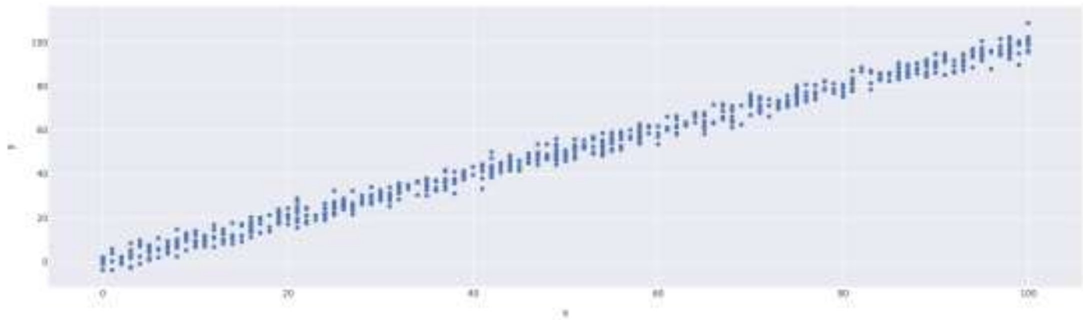
```
[2] # Load the training and test datasets
train_data = pd.read_csv('train.csv')
test_data = pd.read_csv('test.csv')

# Remove rows with missing values
train_data = train_data.dropna()
test_data = test_data.dropna()
```

```
[3] train_data.head()
```

	x	y
0	24.0	21.549452
1	50.0	47.464463
2	15.0	17.218656
3	38.0	36.586398
4	87.0	87.288984

Next steps: View recommended plots

```
[4] px.scatter(x=train_data['x'], y=train_data['y'],template='seaborn')
```




```
[5] # Get training data and target
x_train = train_data['x'].values
y_train = train_data['y'].values

# Get testing data and target
x_test = test_data['x'].values
y_test = test_data['y'].values
```

```
[6]     """
        Standardizes the input data using mean and standard deviation.

        Parameters:
            X_train (numpy.ndarray): Training data.
            X_test (numpy.ndarray): Testing data.

        Returns:
            Tuple of standardized training and testing data.
        """
        # Calculate the mean and standard deviation using the training data
        mean = np.mean(X_train, axis=0)
        std = np.std(X_train, axis=0)

        # Standardize the data
        X_train = (X_train - mean) / std
        X_test = (X_test - mean) / std

        return X_train, X_test

    X_train, X_test = standardize_data(X_train, X_test)
```

```
[7] X_train = np.expand_dims(X_train, axis=-1)
    X_test = np.expand_dims(X_test, axis=-1)
```

```
[8] class LinearRegression:
        """
        Linear Regression Model with Gradient Descent

        Linear regression is a supervised machine learning algorithm used for modeling the relationship
        between a dependent variable (target) and one or more independent variables (features) by fitting
        a linear equation to the observed data.

        This class implements a linear regression model using gradient descent optimization for training.
        It provides methods for model initialization, training, prediction, and model persistence.

        Parameters:
            learning_rate (float): The learning rate used in gradient descent.
            convergence_tol (float, optional): The tolerance for convergence (stopping criterion). Defaults to 1e-6.

        Attributes:
```

```
        Attributes:
[8]         W (numpy.ndarray): Coefficients (weights) for the linear regression model.
            b (float): Intercept (bias) for the linear regression model.

        Methods:
            initialize_parameters(n_features): Initialize model parameters.
            forward(X): Compute the forward pass of the linear regression model.
            compute_cost(predictions): Compute the mean squared error cost.
            backward(predictions): Compute gradients for model parameters.
            fit(X, y, iterations, plot_cost=True): Fit the linear regression model to training data.
            predict(X): Predict target values for new input data.
            save_model(filename=None): Save the trained model to a file using pickle.
            load_model(filename): Load a trained model from a file using pickle.

        Examples:
            >>> from linear_regression import LinearRegression
            >>> model = LinearRegression(learning_rate=0.01)
            >>> model.fit(X_train, y_train, iterations=1000)
            >>> predictions = model.predict(X_test)
        """

        def __init__(self, learning_rate, convergence_tol=1e-6):
            self.learning_rate = learning_rate
            self.convergence_tol = convergence_tol
            self.W = None
            self.b = None

        def initialize_parameters(self, n_features):
            """
            Initialize model parameters.

            Parameters:
                n_features (int): The number of features in the input data.
            """
            self.W = np.random.randn(n_features) * 0.01
            self.b = 0
        def forward(self, X):
            """
            Compute the forward pass of the linear regression model.

            Parameters:
                X (numpy.ndarray): Input data of shape (m, n_features).
```

[8]
```
        Returns:
            numpy.ndarray: Predictions of shape (m,).
        """
        return np.dot(X, self.W) + self.b

    def compute_cost(self, predictions):
        """
        Compute the mean squared error cost.

        Parameters:
            predictions (numpy.ndarray): Predictions of shape (m,).

        Returns:
            float: Mean squared error cost.
        """
        m = len(predictions)
        cost = np.sum(np.square(predictions - self.y)) / (2 * m)
        return cost

    def backward(self, predictions):
        """
        Compute gradients for model parameters.

        Parameters:
            predictions (numpy.ndarray): Predictions of shape (m,).

        Updates:
            numpy.ndarray: Gradient of W.
            float: Gradient of b.
        """
        m = len(predictions)
        self.dW = np.dot(predictions - self.y, self.X) / m
        self.db = np.sum(predictions - self.y) / m
    def fit(self, X, y, iterations, plot_cost=True):
        """
        Fit the linear regression model to the training data.

        Parameters:
            X (numpy.ndarray): Training input data of shape (m, n_features).
            y (numpy.ndarray): Training labels of shape (m,).
            iterations (int): The number of iterations for gradient descent.
            plot_cost (bool, optional): Whether to plot the cost during training. Defaults to True.
```

[8]
```
        Raises:
            AssertionError: If input data and labels are not NumPy arrays or have mismatched shapes.

        Plots:
            Plotly line chart showing cost vs. iteration (if plot_cost is True).
        """
        assert isinstance(X, np.ndarray), "X must be a NumPy array"
        assert isinstance(y, np.ndarray), "y must be a NumPy array"
        assert X.shape[0] == y.shape[0], "X and y must have the same number of samples"
        assert iterations > 0, "Iterations must be greater than 0"

        self.X = X
        self.y = y
        self.initialize_parameters(X.shape[1])
        costs = []

        for i in range(iterations):
            predictions = self.forward(X)
            cost = self.compute_cost(predictions)
            self.backward(predictions)
            self.W -= self.learning_rate * self.dW
            self.b -= self.learning_rate * self.db
            costs.append(cost)

            if i % 100 == 0:
                print(f'Iteration: {i}, Cost: {cost}')

            if i > 0 and abs(costs[-1] - costs[-2]) < self.convergence_tol:
                print(f'Converged after {i} iterations.')
                break

        if plot_cost:
            fig = px.line(y=costs, title="Cost vs Iteration", template="plotly_dark")
            fig.update_layout(
                title_font_color="#41BEE9",
                xaxis=dict(color="#41BEE9", title="Iterations"),
                yaxis=dict(color="#41BEE9", title="Cost")
            )

            fig.show()
```

```python
            fig.show()
    def predict(self, X):
        """
        Predict target values for new input data.

        Parameters:
            X (numpy.ndarray): Input data of shape (m, n_features).

        Returns:
            numpy.ndarray: Predicted target values of shape (m,).
        """
        return self.forward(X)


    def save_model(self, filename=None):
        """
        Save the trained model to a file using pickle.

        Parameters:
            filename (str): The name of the file to save the model to.
        """
        model_data = {
            'learning_rate': self.learning_rate,
            'convergence_tol': self.convergence_tol,
            'W': self.W,
            'b': self.b
        }

        with open(filename, 'wb') as file:
            pickle.dump(model_data, file)

    @classmethod
    def load_model(cls, filename):
        """
        Load a trained model from a file using pickle.

        Parameters:
            filename (str): The name of the file to load the model from.
```



```python
        with open(filename, 'wb') as file:
            pickle.dump(model_data, file)

    @classmethod
    def load_model(cls, filename):
        """
        Load a trained model from a file using pickle.

        Parameters:
            filename (str): The name of the file to load the model from.
```

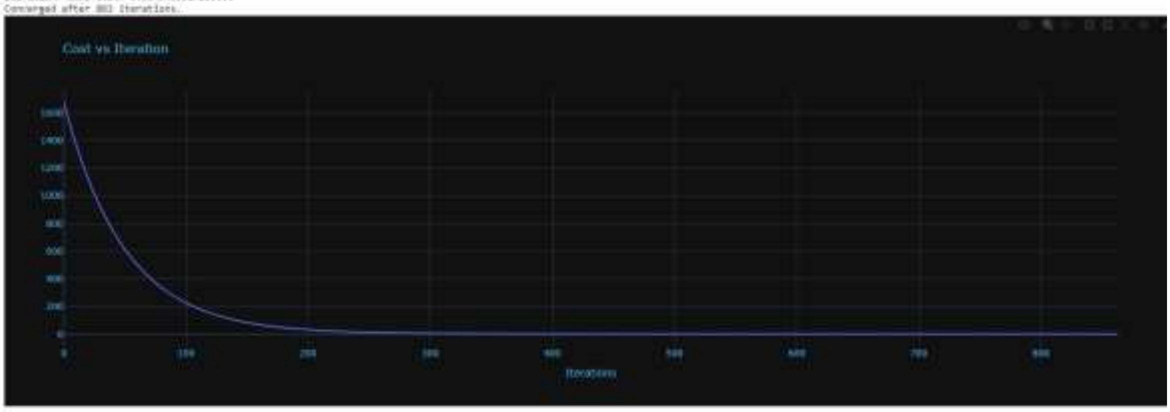


```python
        Returns:
            LinearRegression: An instance of the LinearRegression class with loaded parameters.
        """
        with open(filename, 'rb') as file:
            model_data = pickle.load(file)

        # Create a new instance of the class and initialize it with the loaded parameters
        loaded_model = cls(model_data['learning_rate'], model_data['convergence_tol'])
        loaded_model.W = model_data['W']
        loaded_model.b = model_data['b']

        return loaded_model
```

```python
9] lr = LinearRegression(0.01)
   lr.fit(X_train, y_train, 10000)
```

```
Iteration: 0, Cost: 1670.0184887161677
Iteration: 100, Cost: 227.15535101517312
Iteration: 200, Cost: 33.84101696145528
Iteration: 300, Cost: 7.9408253395546575
Iteration: 400, Cost: 4.4707260872934835
Iteration: 500, Cost: 4.005803317750673
Iteration: 600, Cost: 3.943513116253261
Iteration: 700, Cost: 3.9351674953098015
Iteration: 800, Cost: 3.9340493517293096
Converged after 863 iterations.
```

```
Iteration: 800, Cost: 3.934049351729309
Converged after 803 iterations.
```




```
[10] lr.save_model('model.pkl')
```

```
[11] model = LinearRegression.load_model("model.pkl")
```

```
[12] class RegressionMetrics:
        @staticmethod
        def mean_squared_error(y_true, y_pred):
            """
            Calculate the Mean Squared Error (MSE).

            Args:
                y_true (numpy.ndarray): The true target values.
                y_pred (numpy.ndarray): The predicted target values.

            Returns:
                float: The Mean Squared Error.
            """
            assert len(y_true) == len(y_pred), "Input arrays must have the same length."
            mse = np.mean((y_true - y_pred) ** 2)
            return mse

        @staticmethod
        def root_mean_squared_error(y_true, y_pred):
            """
            Calculate the Root Mean Squared Error (RMSE).

            Args:
                y_true (numpy.ndarray): The true target values.
                y_pred (numpy.ndarray): The predicted target values.

            Returns:
                float: The Root Mean Squared Error.
            """
            assert len(y_true) == len(y_pred), "Input arrays must have the same length."
            mse = RegressionMetrics.mean_squared_error(y_true, y_pred)
            rmse = np.sqrt(mse)
            return rmse

        @staticmethod
        def r_squared(y_true, y_pred):
            """
            Calculate the R-squared (R^2) coefficient of determination.

            Args:
```

```
[12]    @staticmethod
        def r_squared(y_true, y_pred):
            """
            Calculate the R-squared (R^2) coefficient of determination.

            Args:
                y_true (numpy.ndarray): The true target values.
                y_pred (numpy.ndarray): The predicted target values.

            Returns:
                float: The R-squared (R^2) value.
            """
            assert len(y_true) == len(y_pred), "Input arrays must have the same length."
            mean_y = np.mean(y_true)
            ss_total = np.sum((y_true - mean_y) ** 2)
            ss_residual = np.sum((y_true - y_pred) ** 2)
            r2 = 1 - (ss_residual / ss_total)
            return r2
```

```
[13] y_pred = model.predict(X_test)
     mse_value = RegressionMetrics.mean_squared_error(y_test, y_pred)
     rmse_value = RegressionMetrics.root_mean_squared_error(y_test, y_pred)
     r_squared_value = RegressionMetrics.r_squared(y_test, y_pred)

     print(f"Mean Squared Error (MSE): {mse_value}")
     print(f"Root Mean Squared Error (RMSE): {rmse_value}")
     print(f"R-squared (Coefficient of Determination): {r_squared_value}")
```

```
Mean Squared Error (MSE): 9.44266965025894
Root Mean Squared Error (RMSE): 3.07289271701095
R-squared (Coefficient of Determination): 0.9887898724670081
```

```
model.predict([[2]])
```

```
array([107.82727115])
```

6.Logistic Regression

Observation Screenshot:

Implement Logistic Regression Using Appropriate Dataset

function logistic_regression(x, y, learning rate, num_itr):

Initialize random values for weights (w) & bias(b)

for i = 1 to num_itr

logits = X * w + b

pred = sigmoid (logits)

loss = compute_loss (y, pred)

update weights & bias using gradient

Return w, b

function sigmoid (x)

return 1/(1+ exp(-x))

function compute_loss (y_true, y_pred):

loss = - mean(y_true x log(y_pred) + (1+ y_true)* log(1-y_pred))

return loss.

Code and Output:

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

```python
[4] df = pd.read_csv('breast-cancer.csv')
```

```python
[5] df.head()
```

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	...	radius_worst	texture_worst	perimeter_worst	are
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	...	25.38	17.33	184.60	
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	...	24.99	23.41	158.80	
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	...	23.57	25.53	152.50	
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	...	14.91	26.50	98.87	
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	...	22.54	16.67	152.20	

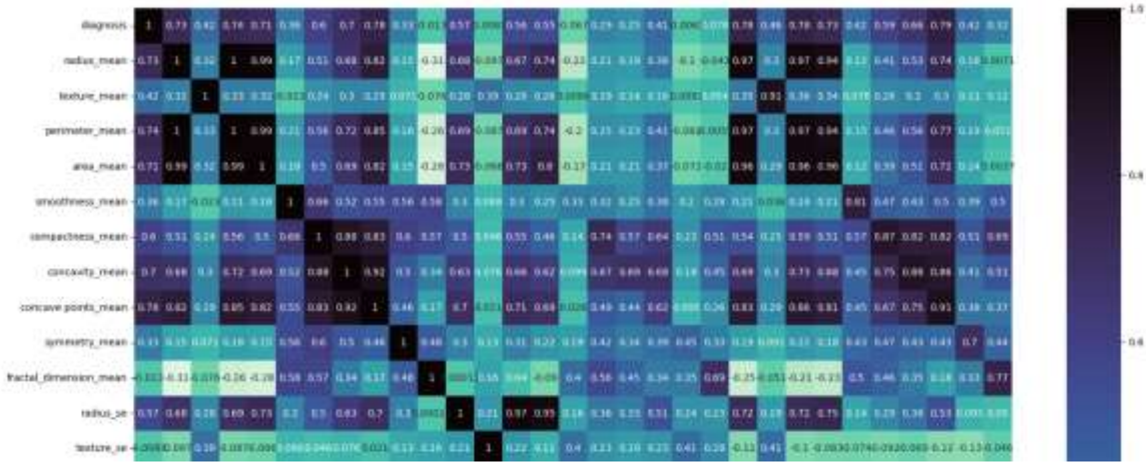
5 rows × 32 columns

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

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

```python
[8] corr = df.corr()
```

```python
[9] plt.figure(figsize=(20,20))
    sns.heatmap(corr, cmap='mako_r',annot=True)
    plt.show()
```



```
# 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
pprint.pprint(names)
```

```
['radius_mean',
 'texture_mean',
 'perimeter_mean',
 'area_mean',
 'smoothness_mean',
 'compactness_mean',
 'concavity_mean',
 'concave 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_worst',
 'concave points_worst',
 'symmetry_worst',
 'fractal_dimension_worst']
```

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

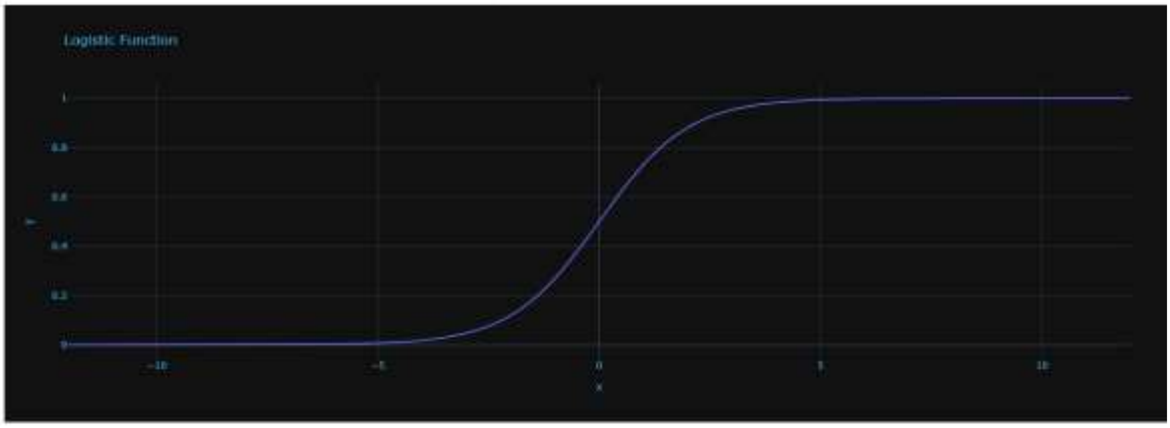
```
[14] def train_test_split(X, y, random_state=42, test_size=0.2):
         """
         Splits the data into training and testing sets.

         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
```

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

```python
[16] def standardize_data(X_train, X_test):
        """
        Standardizes the input data using mean and standard deviation.

        Parameters:
            X_train (numpy.ndarray): Training data.
            X_test (numpy.ndarray): Testing data.

        Returns:
            Tuple of standardized training and testing data.
        """
        # Calculate the mean and standard deviation using the training data
        mean = np.mean(X_train, axis=0)
        std = np.std(X_train, axis=0)

        # Standardize the data
        X_train = (X_train - mean) / std
        X_test = (X_test - mean) / std

        return X_train, X_test

    X_train, X_test = standardize_data(X_train, X_test)
```

```python
[17] def sigmoid(z):
        """
        Compute the sigmoid function for a given input.

        The sigmoid function is a mathematical function used in logistic regression and neural networks
        to map any real-valued number to a value between 0 and 1.

        Parameters:
            z (float or numpy.ndarray): The input value(s) for which to compute the sigmoid.

        Returns:
            float or numpy.ndarray: The sigmoid of the input value(s).

        Example:
            >>> sigmoid(0)
            0.5
        """
        # Compute the sigmoid function using the formula: 1 / (1 + e^(-z)).
        sigmoid_result = 1 / (1 + np.exp(-z))

        # Return the computed sigmoid value.
        return sigmoid_result
```

```python
z = np.linspace(-12, 12, 200)

fig = px.line(x=z, y=sigmoid(z),title='Logistic Function',template="plotly_dark")
fig.update_layout(
    title_font_color="#41BEE9",
    xaxis=dict(color="#41BEE9"),
    yaxis=dict(color="#41BEE9")
)
fig.show()
```




```
[18] class LogisticRegression:
        """
        Logistic Regression model.

        Parameters:
            learning_rate (float): Learning rate for the model.

        Methods:
            initialize_parameter(): Initializes the parameters of the model.
            sigmoid(z): Computes the sigmoid activation function for given input z.
            forward(X): Computes forward propagation for given input X.
        """
```

```
[19]
        def __init__(self, learning_rate=0.0001):
            np.random.seed(1)
            self.learning_rate = learning_rate

        def initialize_parameter(self):
            """
            Initializes the parameters of the model.
            """
            self.W = np.zeros(self.X.shape[1])
            self.b = 0.0


        def forward(self, X):
            """
            Computes forward propagation for given input X.

            Parameters:
                X (numpy.ndarray): Input array.

            Returns:
                numpy.ndarray: Output array.
            """
    #         print(X.shape, self.W.shape)
            Z = np.matmul(X, self.W) + self.b
            A = sigmoid(Z)
            return A

        def compute_cost(self, predictions):
            """
            Computes the cost function for given predictions.

            Parameters:
                predictions (numpy.ndarray): Predictions of the model.

            Returns:
                float: Cost of the model.
            """
            m = self.X.shape[0]  # number of training examples
            # compute the cost
            cost = np.sum((-np.log(predictions + 1e-8) * self.y) + (-np.log(1 - predictions + 1e-8)) * (
                    1 - self.y))  # we are adding small value epsilon to avoid log of 0
```

[19]

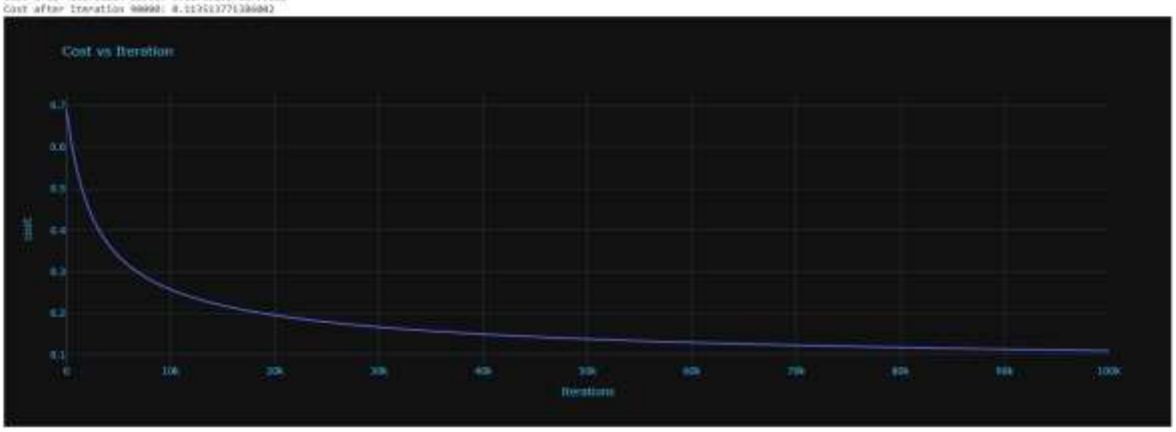
```
            float: cost of the model.
        """
        m = self.X.shape[0]  # number of training examples
        # compute the cost
        cost = np.sum((-np.log(predictions + 1e-8) * self.y) + (-np.log(1 - predictions + 1e-8)) * (
                1 - self.y))  # we are adding small value epsilon to avoid log of 0
        cost = cost / m
        return cost
    def compute_gradient(self, predictions):
        """
        Computes the gradients for the model using given predictions.

        Parameters:
            predictions (numpy.ndarray): Predictions of the model.
        """
        # get training shape
        m = self.X.shape[0]

        # compute gradients
        self.dW = np.matmul(self.X.T, (predictions - self.y))
        self.dW = np.array([np.mean(grad) for grad in self.dW])

        self.db = np.sum(np.subtract(predictions, self.y))

        # scale gradients
        self.dW = self.dW * 1 / m
        self.db = self.db * 1 / m


    def fit(self, X, y, iterations, plot_cost=True):
        """
        Trains the model on given input X and labels y for specified iterations.

        Parameters:
            X (numpy.ndarray): Input features array of shape (n_samples, n )
            y (numpy.ndarray): Labels array of shape (n_samples, 1)
            iterations (int): Number of iterations for training.
            plot_cost (bool): Whether to plot cost over iterations or not.

        Returns:
            None.
        """
        self.X = X
```

```
19]     self.X = X
        self.y = y

        self.initialize_parameter()

        costs = []
        for i in range(iterations):
            # forward propagation
            predictions = self.forward(self.X)

            # compute cost
            cost = self.compute_cost(predictions)
            costs.append(cost)

            # compute gradients
            self.compute_gradient(predictions)

            # update parameters
            self.W = self.W - self.learning_rate * self.dW
            self.b = self.b - self.learning_rate * self.db

            # print cost every 100 iterations
            if i % 10000 == 0:
                print("Cost after iteration {}: {}".format(i, cost))

        if plot_cost:
            fig = px.line(y=costs,title="Cost vs Iteration",template="plotly_dark")
            fig.update_layout(
                title_font_color="#41BEE9",
                xaxis=dict(color="#41BEE9",title="Iterations"),
                yaxis=dict(color="#41BEE9",title="cost")
            )
            fig.show()
    def predict(self, X):
        """
        Predicts the labels for given input X.

        Parameters:
            X (numpy.ndarray): Input features array.

        Returns:
            numpy.ndarray: Predicted labels.
        """
```

```python
[19]        predictions = self.forward(X)
            return np.round(predictions)


        def save_model(self, filename=None):
            """
            Save the trained model to a file using pickle.

            Parameters:
                filename (str): The name of the file to save the model to.
            """
            model_data = {
                'learning_rate': self.learning_rate,
                'W': self.W,
                'b': self.b
            }

            with open(filename, 'wb') as file:
                pickle.dump(model_data, file)

        @classmethod
        def load_model(cls, filename):
            """
            Load a trained model from a file using pickle.

            Parameters:
                filename (str): The name of the file to load the model from.

            Returns:
                LogisticRegression: An instance of the LogisticRegression class with loaded parameters.
            """
            with open(filename, 'rb') as file:
                model_data = pickle.load(file)

            # Create a new instance of the class and initialize it with the loaded parameters
            loaded_model = cls(model_data['learning_rate'])
            loaded_model.W = model_data['W']
            loaded_model.b = model_data['b']

            return loaded_model
```

```python
lg = LogisticRegression()
lg.fit(X_train, y_train,100000)
```

```
Cost after iteration 0: 0.69314718055[illegible]
Cost after iteration 10000: 0.257[illegible]
Cost after iteration 20000: 0.195[illegible]
Cost after iteration 30000: 0.16[illegible]
Cost after iteration 40000: 0.14[illegible]
Cost after iteration 50000: 0.13[illegible]
Cost after iteration 60000: 0.12[illegible]
Cost after iteration 70000: 0.122[illegible]
Cost after iteration 80000: 0.117[illegible]
Cost after iteration 90000: 0.113[illegible]
```



```
[22] lg.save_model("model.pkl")
```

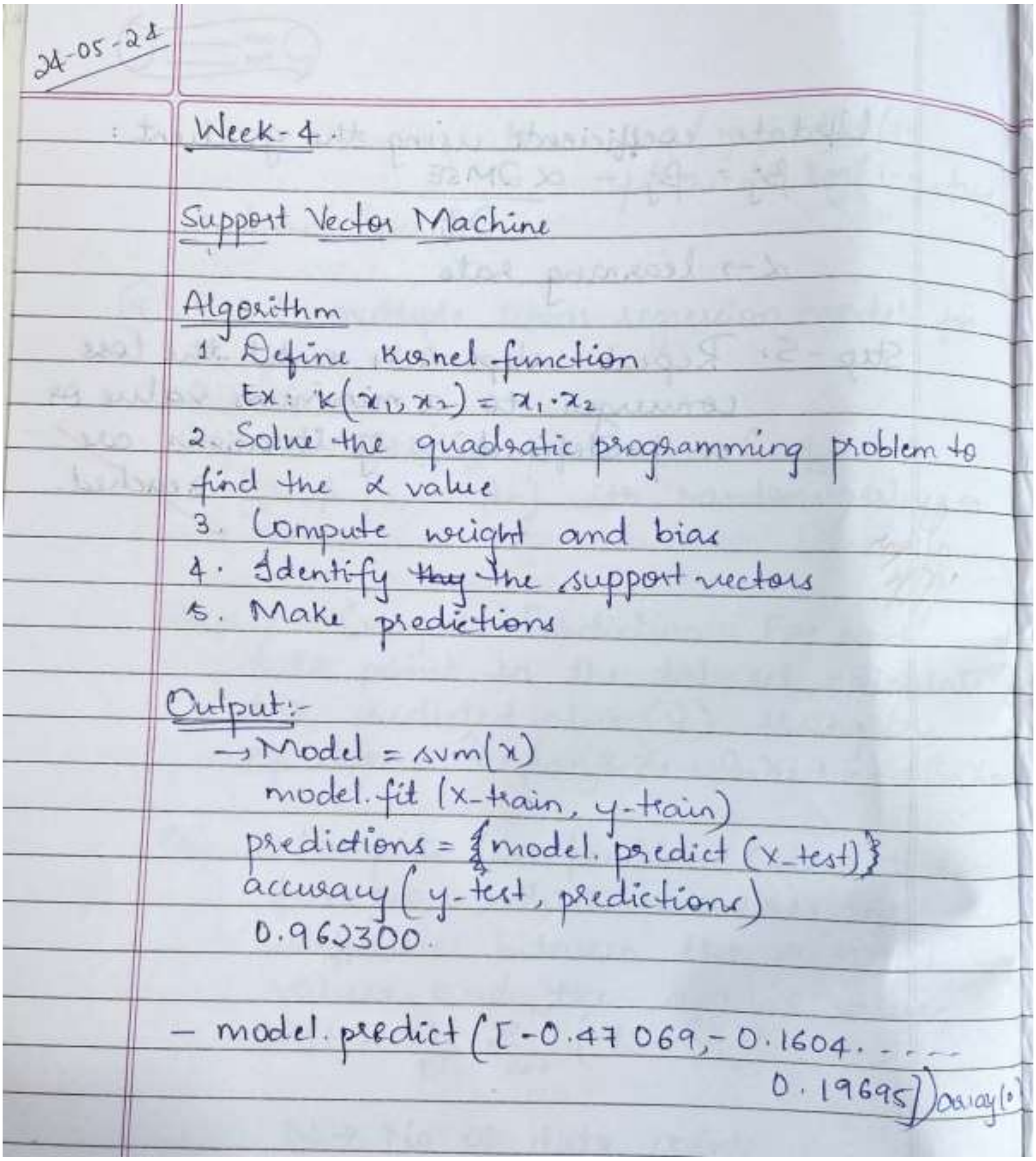
```
[ ] class ClassificationMetrics:
        @staticmethod
        def accuracy(y_true, y_pred):
            """
            Computes the accuracy of a classification model.

            Parameters:
            y_true (numpy array): A numpy array of true labels for each data point.
            y_pred (numpy array): A numpy array of predicted labels for each data point.

            Returns:
            float: The accuracy of the model, expressed as a percentage.
            """
            y_true = y_true.flatten()
            total_samples = len(y_true)
            correct_predictions = np.sum(y_true == y_pred)
            return (correct_predictions / total_samples)

        @staticmethod
        def precision(y_true, y_pred):
            """
            Computes the precision of a classification model.

            Parameters:
            y_true (numpy array): A numpy array of true labels for each data point.
            y_pred (numpy array): A numpy array of predicted labels for each data point.

            Returns:
            float: The precision of the model, which measures the proportion of true positive predictions
            out of all positive predictions made by the model.
            """
            true_positives = np.sum((y_true == 1) & (y_pred == 1))
            false_positives = np.sum((y_true == 0) & (y_pred == 1))
            return true_positives / (true_positives + false_positives)
```

```
[23]    @staticmethod
        def recall(y_true, y_pred):
            """
            Computes the recall (sensitivity) of a classification model.

            Parameters:
            y_true (numpy array): A numpy array of true labels for each data point.
            y_pred (numpy array): A numpy array of predicted labels for each data point.

            Returns:
            float: The recall of the model, which measures the proportion of true positive predictions
            out of all actual positive instances in the dataset.
            """
            true_positives = np.sum((y_true == 1) & (y_pred == 1))
            false_negatives = np.sum((y_true == 1) & (y_pred == 0))
            return true_positives / (true_positives + false_negatives)

        @staticmethod
        def f1_score(y_true, y_pred):
            """
            Computes the F1-score of a classification model.

            Parameters:
            y_true (numpy array): A numpy array of true labels for each data point.
            y_pred (numpy array): A numpy array of predicted labels for each data point.

            Returns:
            float: The F1-score of the model, which is the harmonic mean of precision and recall.
            """
            precision_value = ClassificationMetrics.precision(y_true, y_pred)
            recall_value = ClassificationMetrics.recall(y_true, y_pred)
            return 2 * (precision_value * recall_value) / (precision_value + recall_value)
```

```
[24] model = LogisticRegression.load_model("model.pkl")
```

7.Build Support vector machine model for a given dataset Algorithm

Observation Screenshot:


24-05-24

Week-4.

Support Vector Machine

Algorithm

1. Define Kernel function
   Ex: $K(x_1, x_2) = x_1 \cdot x_2$
2. Solve the quadratic programming problem to find the α value
3. Compute weight and bias
4. Identify ~~they~~ the support vectors
5. Make predictions

Output:-

→ Model = svm(x)
model.fit (x-train, y-train)
predictions = {model. predict (x_test)}
accuracy (y-test, predictions)
0.962300

– model. predict ([-0.47 069, -0.1604. . . . .
0. 19695]) array(0

Code and Output:

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

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

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

```
[3] df = pd.read_csv('/content/drive/MyDrive/breast-cancer.csv')
    df.head()
```

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	...	rad
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	...	
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	...	
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	...	
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	...	
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	...	

5 rows × 32 columns

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

```
[6] df.describe().T
```

	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

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

```
[8] corr = df.corr()
```

```
[10] # 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', 'concave points_mean', 'symmetry,
```

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

```
[12] 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
```

```
[13] X = scale(X)
```

```
[14] 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
```

```
[15] 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 and validatin
```

```
[18] class SVM:
        """
        A Support Vector Machine (SVM) implementation using gradient descent.

        Parameters:
        -----------
        iterations : int, default=1000
            The number of iterations for gradient descent.
        lr : float, default=0.01
            The learning rate for gradient descent.
        lambdaa : float, default=0.01
            The regularization parameter.

        Attributes:
        -----------
        lambdaa : float
            The regularization parameter.
        iterations : int
            The number of iterations for gradient descent.
        lr : float
            The learning rate for gradient descent.
        w : numpy array
            The weights.
        b : float
            The bias.

        Methods:
        --------
        initialize_parameters(X)
            Initializes the weights and bias.
        gradient_descent(X, y)
            Updates the weights and bias using gradient descent.
```

```
[18]    update_parameters(dw, db)
            Updates the weights and bias.
        fit(X, y)
            Fits the SVM to the data.
        predict(X)
            Predicts the labels for the given data.

        """

        def __init__(self, iterations=1000, lr=0.01, lambdaa=0.01):
            """
            Initializes the SVM model.

            Parameters:
            -----------
            iterations : int, default=1000
                The number of iterations for gradient descent.
            lr : float, default=0.01
                The learning rate for gradient descent.
            lambdaa : float, default=0.01
                The regularization parameter.
            """
            self.lambdaa = lambdaa
            self.iterations = iterations
            self.lr = lr
            self.w = None
            self.b = None
        def initialize_parameters(self, X):
            """
            Initializes the weights and bias.

            Parameters:
            -----------
```

[18]

```
        X : numpy array
            The input data.
        """
        m, n = X.shape
        self.w = np.zeros(n)
        self.b = 0

    def gradient_descent(self, X, y):
        """
        Updates the weights and bias using gradient descent.

        Parameters:
        -----------
        X : numpy array
            The input data.
        y : numpy array
            The target values.
        """
        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):
        """
        Updates the weights and bias.

        Parameters:
```

[18]

```
        dw : numpy array
            The change in weights.
        db : float
            The change in bias.
        """
        self.w = self.w - self.lr * dw
        self.b = self.b - self.lr * db
    def fit(self, X, y):
        """
        Fits the SVM to the data.

        Parameters:
        -----------
        X : numpy array
            The input data.
        y : numpy array
            The target values.
        """
        self.initialize_parameters(X)
        for i in range(self.iterations):
            self.gradient_descent(X, y)


    def predict(self, X):
        """
        Predicts the class labels for the test data.

        Parameters
        ----------
        X : array-like, shape (n_samples, n_features)
            The input data.

        Returns
```

```
[18]        Returns
            -------
            y_pred : array-like, shape (n_samples,)
                The predicted class labels.

            """
            # 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
```

```
[19] def accuracy(y_true, y_pred):
        """
        Computes the accuracy of a classification model.

        Parameters:
        ----------
            y_true (numpy array): A numpy array of true labels for each data point.
            y_pred (numpy array): A numpy array of predicted labels for each data point.

        Returns:
        ----------
            float: The accuracy of the model
        """
        total_samples = len(y_true)
        correct_predictions = np.sum(y_true == y_pred)
        return (correct_predictions / total_samples)
```

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

     accuracy(y_test, predictions)
```

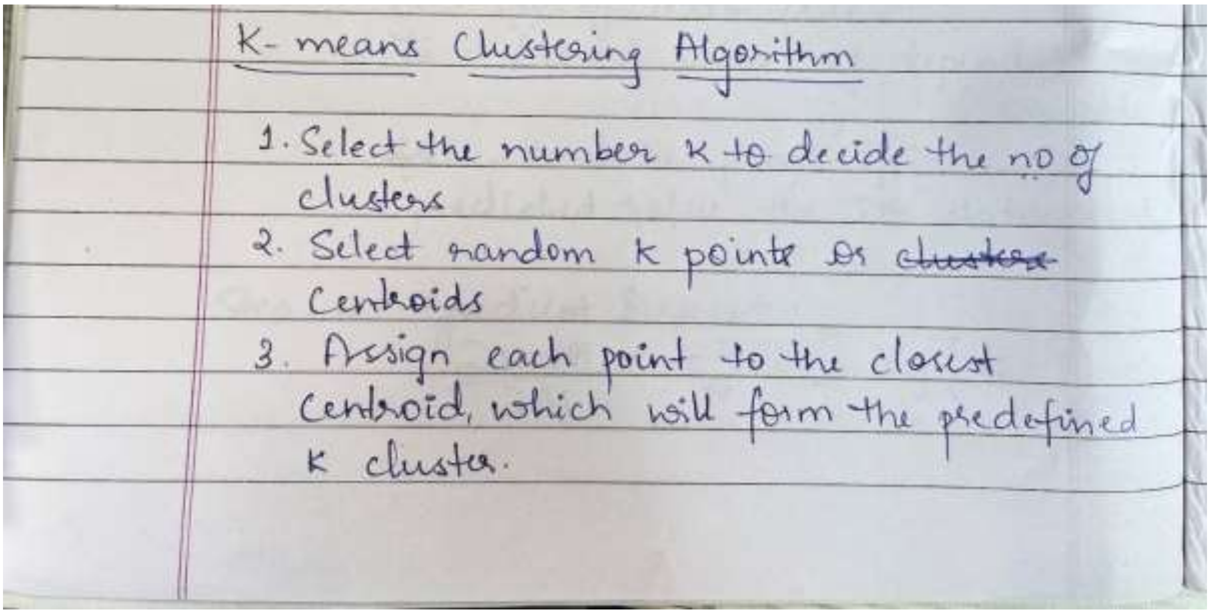
```
0.9823008849557522
```

```
[28] model.predict([-0.47069438, -0.16048584, -0.44810956, -0.49199876,  0.23411429,
                 0.02765051, -0.10984741, -0.27623152,  0.41394897, -0.03274296,
                -0.18269561, -0.22105292, -0.35591235, -0.16192949, -0.23133322,
                -0.26903951, -0.16890536, -0.33393537, -0.35629925,  0.4485028 ,
                -0.10474068, -0.02441212, -0.19956318,  0.18320441,  0.19695794])
```

```
array(0)
```

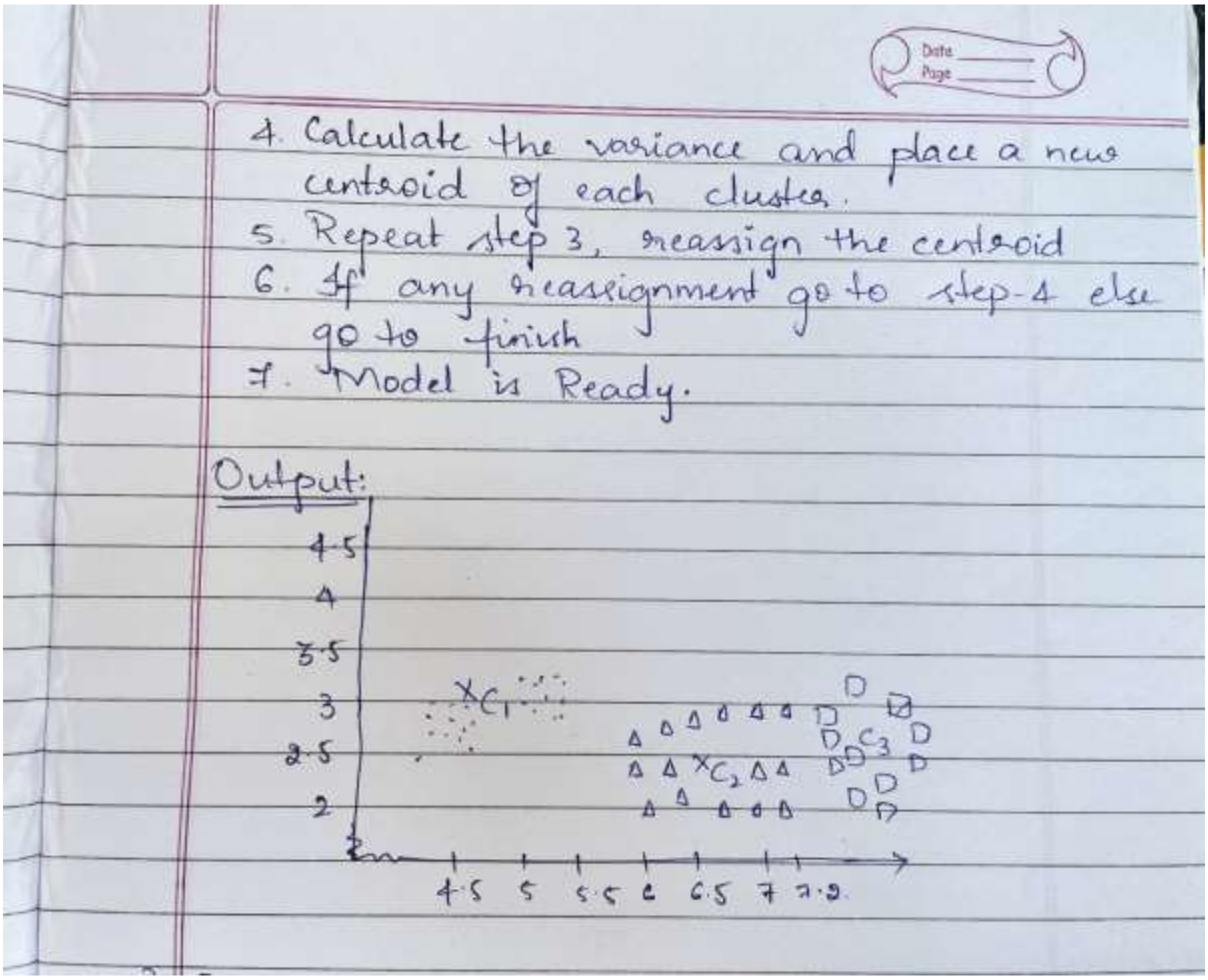
8.Build k-Means algorithm to cluster a set of data stored in a .CSV file.

Observation Screenshot:



K- means Clustering Algorithm

1. Select the number K to decide the no of clusters
2. Select random K points or ~~clusters~~ Centroids
3. Assign each point to the closest centroid, which will form the predefined K cluster.



4. Calculate the variance and place a new centroid of each cluster.
5. Repeat step 3, reassign the centroid
6. If any reassignment go to step-4 else go to finish
7. Model is Ready.

Output:

Code and Output:

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

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

```
[2] import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    import plotly.express as px
    import seaborn as sns
    import plotly.graph_objects as go
```

```
[3] iris = pd.read_csv("/content/drive/MyDrive/Iris.csv") #Load Data
    iris.drop('Id',inplace=True,axis=1) #Drop Id column
```

```
[4] X = iris.iloc[:,:-1] #Set our training data

    y = iris.iloc[:,-1] #We'll use this just for visualization as clustering doesn't require labels
```

```
[5] class Kmeans:
        """
        K-Means clustering algorithm implementation.

        Parameters:
            K (int): Number of clusters

        Attributes:
            K (int): Number of clusters
            centroids (numpy.ndarray): Array containing the centroids of each cluster
```

```
[5]     Methods:
            __init__(self, K): Initializes the Kmeans instance with the specified number of clusters.
            initialize_centroids(self, X): Initializes the centroids for each cluster by selecting K random points from the dataset.
            assign_points_centroids(self, X): Assigns each point in the dataset to the nearest centroid.
            compute_mean(self, X, points): Computes the mean of the points assigned to each centroid.
            fit(self, X, iterations=10): Clusters the dataset using the K-Means algorithm.
        """

        def __init__(self, K):
            assert K > 0, "K should be a positive integer."
            self.K = K

        def initiallize_centroids(self, X):
            assert X.shape[0] >= self.K, "Number of data points should be greater than or equal to K."

            randomized_X = np.random.permutation(X.shape[0])
            centroid_idx = randomized_X[:self.K] # get the indices for the centroids
            self.centroids = X[centroid_idx] # assign the centroids to the selected points

        def assign_points_centroids(self, X):
            """
            Assign each point in the dataset to the nearest centroid.

            Parameters:
            X (numpy.ndarray): dataset to cluster

            Returns:
            numpy.ndarray: array containing the index of the centroid for each point
            """
            X = np.expand_dims(X, axis=1) # expand dimensions to match shape of centroids
            distance = np.linalg.norm((X - self.centroids), axis=-1) # calculate Euclidean distance between each point and each centroid
            points = np.argmin(distance, axis=1) # assign each point to the closest centroid
            assert len(points) == X.shape[0], "Number of assigned points should equal the number of data points."
```

```
points = np.argmin(distance, axis=1) # assign each point to the closest centroid
[5]     assert len(points) == X.shape[0], "Number of assigned points should equal the number of data points."
        return points

    def compute_mean(self, X, points):
        """
        Compute the mean of the points assigned to each centroid.

        Parameters:
        X (numpy.ndarray): dataset to cluster
        points (numpy.ndarray): array containing the index of the centroid for each point

        Returns:
        numpy.ndarray: array containing the new centroids for each cluster
        """
        centroids = np.zeros((self.K, X.shape[1])) # initialize array to store centroids
        for i in range(self.K):
            centroid_mean = X[points == i].mean(axis=0) # calculate mean of the points assigned to the current centroid
            centroids[i] = centroid_mean # assign the new centroid to the mean of its points
        return centroids

    def fit(self, X, iterations=10):
        """
        Cluster the dataset using the K-Means algorithm.

        Parameters:
        X (numpy.ndarray): dataset to cluster
        iterations (int): number of iterations to perform (default=10)

        Returns:
        numpy.ndarray: array containing the final centroids for each cluster
        numpy.ndarray: array containing the index of the centroid for each point
        """
        self.initialize_centroids(X) # initialize the centroids
```

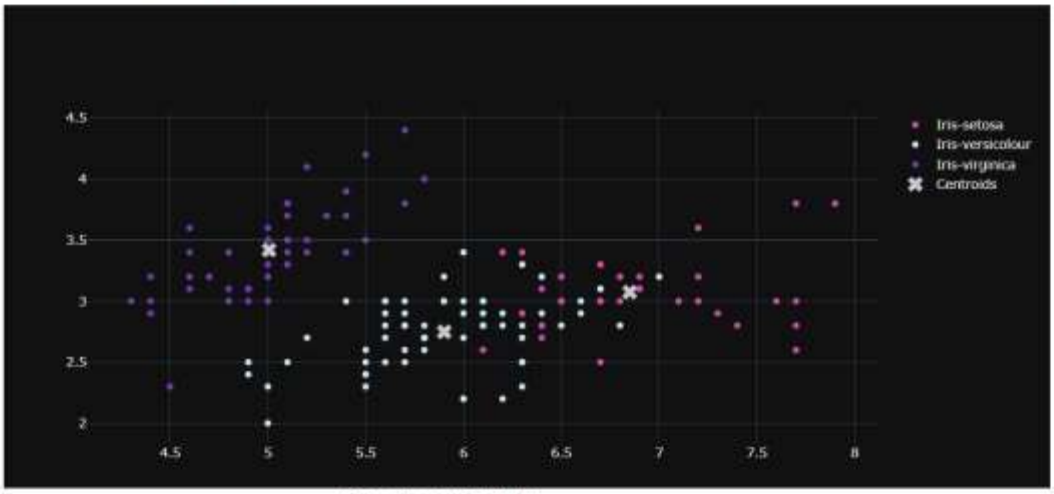
```
[5]     """
        self.initialize_centroids(X) # initialize the centroids
        for i in range(iterations):
            points = self.assign_points_centroids(X) # assign each point to the nearest centroid
            self.centroids = self.compute_mean(X, points) # compute the new centroids based on the mean of their points

            # Assertions for debugging and validation
            assert len(self.centroids) == self.K, "Number of centroids should equal K."
            assert X.shape[1] == self.centroids.shape[1], "Dimensionality of centroids should match input data."
            assert max(points) < self.K, "Cluster index should be less than K."
            assert min(points) >= 0, "Cluster index should be non-negative."

        return self.centroids, points
```

```
[6] X = X.values
```

```
[7] kmeans = Kmeans(3)

    centroids, points = kmeans.fit(X, 1000)
```

```
[8] fig = go.Figure()
    fig.add_trace(go.Scatter(
        x=X[points == 0, 0], y=X[points == 0, 1],
        mode='markers',marker_color='#DB4CB2',name='Iris-setosa'
    ))

    fig.add_trace(go.Scatter(
        x=X[points == 1, 0], y=X[points == 1, 1],
        mode='markers',marker_color='#c9e9f6',name='Iris-versicolour'
    ))
```

```
))
[8]
fig.add_trace(go.Scatter(
    x=X[points == 2, 0], y=X[points == 2, 1],
    mode='markers',marker_color='#7D3AC1',name='Iris-virginica'
))

fig.add_trace(go.Scatter(
    x=centroids[:, 0], y=centroids[:,1],
    mode='markers',marker_color='#CAC9CD',marker_symbol=4,marker_size=13,name='Centroids'
))
fig.update_layout(template='plotly_dark',width=1000, height=500,)
```



9.Implement Dimensionality reduction using Principle Component Analysis (PCA)

Observation Screenshot:

3] Principal Component Analysis

Algorithm

1. Calculate mean
2. Calculation of covariance matrix
3. Eigen values of covariance matrix
4. Computation of the Eigen vector - unit eigen vector
5. Computation of first principal components
6. Geometric meaning of first principal component

Output

pca.explained_variance_ratio

array([0.9837428, 0.01620498])

Code and Output:

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

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

```
[2] import seaborn as sns
    import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    import plotly.express as px
    import plotly.graph_objects as go
    from plotly.subplots import make_subplots
```

```
[3] df = pd.read_csv('/content/drive/MyDrive/breast-cancer.csv')
    df.head()
```

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	...	radius_worst
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	...	25.38
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	...	24.99
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	...	23.57
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	...	14.91
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	...	22.54

5 rows × 32 columns

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

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

```
[6] corr = df.corr()
```

```
[8] # 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', 'concave p
```

```
[9] X = df[names].values
```



```
[9] X = df[names].values
```



```
[11] class PCA:
         """
         Principal Component Analysis (PCA) class for dimensionality reduction.
         """

         def __init__(self, n_components):
             """
             Constructor method that initializes the PCA object with the number of components to retain.

             Args:
             - n_components (int): Number of principal components to retain.
             """
             self.n_components = n_components
         def fit(self, X):
             """
             Fits the PCA model to the input data and computes the principal components.

             Args:
             - X (numpy.ndarray): Input data matrix with shape (n_samples, n_features).
             """
             # Compute the mean of the input data along each feature dimension.
             mean = np.mean(X, axis=0)

             # Subtract the mean from the input data to center it around zero.
             X = X - mean

             # Compute the covariance matrix of the centered input data.
             cov = np.cov(X.T)
```

[11]
```
        # Compute the covariance matrix of the centered input data.
        cov = np.cov(X.T)

        # Compute the eigenvectors and eigenvalues of the covariance matrix.
        eigenvalues, eigenvectors = np.linalg.eigh(cov)
        # Reverse the order of the eigenvalues and eigenvectors.
        eigenvalues = eigenvalues[::-1]
        eigenvectors = eigenvectors[:,::-1]

        # Keep only the first n_components eigenvectors as the principal components.
        self.components = eigenvectors[:,:self.n_components]

        # Compute the explained variance ratio for each principal component.
        # Compute the total variance of the input data
        total_variance = np.sum(np.var(X, axis=0))

        # Compute the variance explained by each principal component
        self.explained_variances = eigenvalues[:self.n_components]

        # Compute the explained variance ratio for each principal component
        self.explained_variance_ratio_ = self.explained_variances / total_variance
    def transform(self, X):
        """
        Transforms the input data by projecting it onto the principal components.

        Args:
        - X (numpy.ndarray): Input data matrix with shape (n_samples, n_features).

        Returns:
        - transformed_data (numpy.ndarray): Transformed data matrix with shape (n_samples, n_components).
        """
        # Center the input data around zero using the mean computed during the fit step.
        X = X - np.mean(X, axis=0)
```

[11]
```
        # Project the centered input data onto the principal components.
        transformed_data = np.dot(X, self.components)

        return transformed_data

    def fit_transform(self, X):
        """
        Fits the PCA model to the input data and computes the principal components then
        transforms the input data by projecting it onto the principal components.

        Args:
        - X (numpy.ndarray): Input data matrix with shape (n_samples, n_features).
        """
        self.fit(X)
        transformed_data = self.transform(X)
        return transformed_data
```

[12]
```
pca = PCA(2)
```

[13]
```
pca.fit(X)
```

[14]
```
pca.explained_variance_ratio_
```

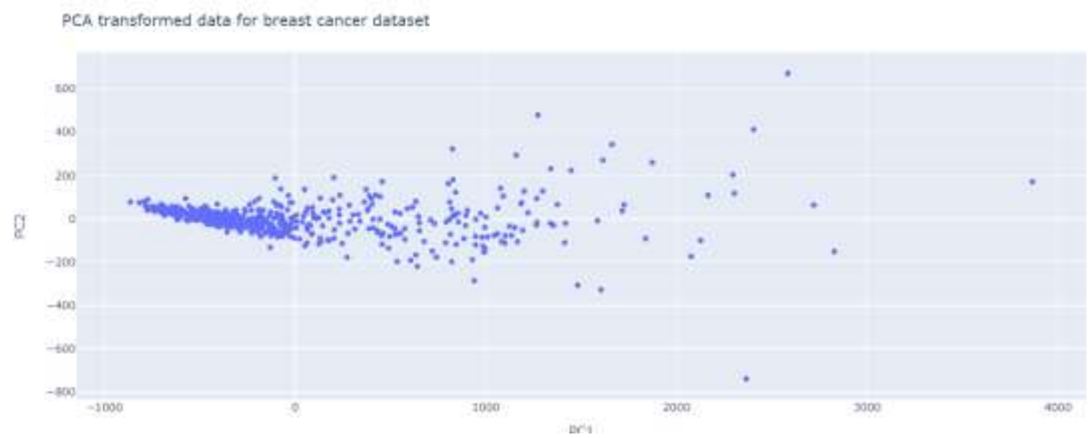
```
array([0.98377428, 0.01620498])
```

[15]
```
X_transformed = pca.transform(X)
```

[16]
```
X_transformed[:,1].shape
```

```
(569,)
```

```
fig = px.scatter(x=X_transformed[:,0], y=X_transformed[:,1])
fig.update_layout(
    title="PCA transformed data for breast cancer dataset",
    xaxis_title="PC1",
    yaxis_title="PC2"
)
fig.show()
```



10. Build Artificial Neural Network model with back propagation on a given dataset
Observation Screenshot:

31-05-24

WEEK-5:-

1] ANN with backpropagation for a given dataset

~~Backpropagation Algorithm (training example, η, η_{in}, η_{out}, η_{hidden})~~
~~For each $(\vec{x}, \vec{t})$ in training examples, Do~~
~~1. Input the instance $\vec{x}$, to the network and compute the output O_u of every unit u in the network~~

2. Backpropagation (training example, η, η_{in}, η_{out}, η_{hidden})

- Create a feed-forward network with n_{in} inputs, η_{hidden} hidden units and η_{out} output units
- Initialize all network weights to small random number.
- Until the termination Condition is met, Do
  - → For each $(\vec{x}, \vec{t})$ in training examples, Do
    1. Input the instance $\vec{x}$, to the network & compute the output O_u of every unit u in the network
  - → Propagate the errors backward through the network.
    2. For each ~~instance~~ network output unit k, calculate its error term δ_k
       $$\delta_k \leftarrow O_k(1 - O_k)(t_k - O_k)$$

3. For each hidden unit h, calculate its error term δ_h

$$\delta_h \leftarrow O_h(1 - O_h) \sum_{k \in Outputs} w_{h,k} \delta_k$$

4. Update each network weight w_{ji}:

$$w_{ji} \leftarrow w_{ji} + \Delta w_{ji}$$

where $\Delta w_{ji} = \eta \delta_j x_{ij}$

Code and Output:

```
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)
```

```
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)
```

```
[4] 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))
```

```
[5] 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
```

```
[6] 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)
```

```
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
```

```
[8] 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]
```

```
[9] 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)
```

```
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_train),
                                                                                     training_correct_answers/len(x_train),"Duke breast cancer"))
```

```
MLP Correct answers while learning: 44 / 77 (Accuracy = 0.5714285714285714) on Duke breast cancer database.
```

```
[11] 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), "Duke breast cancer"))
```

```
MLP Correct answers while testing: 8 / 9 (Accuracy = 0.8888888888888888) on Duke breast cancer database
```

11a. Implement Random forest ensemble method on a given dataset
Observation Screenshot:

2. Random Forest Ensemble for a given dataset.
Random Forest Algorithm.
Step-1: Select random k data points from the training set
Step-2: Build the decision trees associated with the selected data points
Step-3: Choose the number N for decision trees that you want to build.
Step-4: Repeat step-1 & 2.
Step-5: For new data points, find the predictions of each decision tree and assign the new data points to the category that wins the majority votes.

Code and Output:

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

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

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

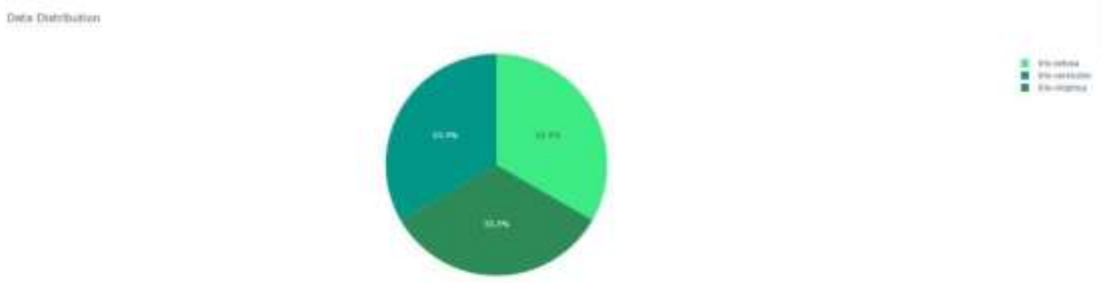
```
[19] iris = pd.read_csv("/content/drive/MyDrive/Iris.csv") #Load Data
     iris.drop('Id',inplace=True,axis=1) #Drop Id column
```

```
[20] iris.head().style.background_gradient(cmap =sns.light_palette("seagreen", as_cmap=True)
     )
```

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	5.100000	3.500000	1.400000	0.200000	Iris-setosa
1	4.900000	3.000000	1.400000	0.200000	Iris-setosa
2	4.700000	3.200000	1.300000	0.200000	Iris-setosa
3	4.600000	3.100000	1.500000	0.200000	Iris-setosa
4	5.000000	3.600000	1.400000	0.200000	Iris-setosa

```
[21] X_df = iris.iloc[:,:-1] #Set our training dataframe

     y_df = iris.iloc[:,-1] # Set our training labels dataframe
```

```
[illegible]
```




```
[illegible]
```

```
[23] iris['Species'] = iris['Species'].astype("category")
     codes = iris['Species'].cat.codes
```

```
[24] def train_test_split(X, y, random_state=42, 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
```

```
[25] X = iris.iloc[:, :-1].values
     y = iris.iloc[:, -1].values.reshape(-1,1)
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.2, random_state=41)
```

```
[26] from sklearn.tree import DecisionTreeClassifier
     m = DecisionTreeClassifier()
```

```
[27] class RandomForest:
         """
         A random forest classifier.

         Parameters
         ----------
         n_trees : int, default=7
             The number of trees in the random forest.
         max_depth : int, default=7
             The maximum depth of each decision tree in the random forest.
         min_samples : int, default=2
             The minimum number of samples required to split an internal node
             of each decision tree in the random forest.

         Attributes
         ----------
         n_trees : int
             The number of trees in the random forest.
         max_depth : int
             The maximum depth of each decision tree in the random forest.
         min_samples : int
             The minimum number of samples required to split an internal node
             of each decision tree in the random forest.
         trees : list of DecisionTreeClassifier
             The decision trees in the random forest.
         """

         def __init__(self, n_trees=7, max_depth=7, min_samples=2):
             """
             Initialize the random forest classifier.
```

```
[ ]         The decision trees in the random forest.
        """

    def __init__(self, n_trees=7, max_depth=7, min_samples=2):
        """
        Initialize the random forest classifier.

        Parameters
        ----------
        n_trees : int, default=7
            The number of trees in the random forest.
        max_depth : int, default=7
            The maximum depth of each decision tree in the random forest.
        min_samples : int, default=2
            The minimum number of samples required to split an internal node
            of each decision tree in the random forest.
        """
        self.n_trees = n_trees
        self.max_depth = max_depth
        self.min_samples = min_samples
        self.trees = []

    def fit(self, X, y):
        """
        Build a random forest classifier from the training set (X, y).

        Parameters
        ----------
        X : array-like of shape (n_samples, n_features)
            The training input samples.
        y : array-like of shape (n_samples,)
            The target values.

        Returns
        -------
        self : object
            Returns self.
        """
        # Create an empty list to store the trees.
        self.trees = []
        # Concatenate X and y into a single dataset.
        dataset = np.concatenate((X, y.reshape(-1, 1)), axis=1)
        # Loop over the number of trees.
```

```
[27]    """
        # Create an empty list to store the trees.
        self.trees = []
        # Concatenate X and y into a single dataset.
        dataset = np.concatenate((X, y.reshape(-1, 1)), axis=1)
        # Loop over the number of trees.
        for _ in range(self.n_trees):
            # Create a decision tree instance.
            tree = DecisionTreeClassifier(max_depth=self.max_depth, min_samples_split=self.min_samples)
            # Sample from the dataset with replacement (bootstrapping).
            dataset_sample = self.bootstrap_samples(dataset)
            # Get the X and y samples from the dataset sample.
            X_sample, y_sample = dataset_sample[:, :-1], dataset_sample[:, -1]
            # Fit the tree to the X and y samples.
            tree.fit(X_sample, y_sample)
            # Store the tree in the list of trees.
            self.trees.append(tree)
        return self

    def bootstrap_samples(self, dataset):
        """
        Bootstrap the dataset by sampling from it with replacement.

        Parameters
        ----------
        dataset : array-like of shape (n_samples, n_features + 1)
            The dataset to bootstrap.

        Returns
        -------
        dataset_sample : array-like of shape (n_samples, n_features + 1)
            The bootstrapped dataset sample.
        """
        # Get the number of samples in the dataset.
        n_samples = dataset.shape[0]
        # Generate random indices to index into the dataset with replacement.
        np.random.seed(1)
        indices = np.random.choice(n_samples, n_samples, replace=True)
        # Return the bootstrapped dataset sample using the generated indices.
        dataset_sample = dataset[indices]
        return dataset_sample

    def most_common_label(self, y):
```

[27]

```python
    def most_common_label(self, y):
        """
        Return the most common label in an array of labels.

        Parameters
        ----------
        y : array-like of shape (n_samples,)
            The array of labels.

        Returns
        -------
        most_occuring_value : int or float
            The most common label in the array.
        """
        y = list(y)
        # get the highest present class in the array
        most_occuring_value = max(y, key=y.count)
        return most_occuring_value

    def predict(self, X):
        """
        Predict class for X.

        Parameters
        ----------
        X : array-like of shape (n_samples, n_features)
            The input samples.

        Returns
        -------
        majority_predictions : array-like of shape (n_samples,)
            The predicted classes.
        """
        #get prediction from each tree in the tree list on the test data
        predictions = np.array([tree.predict(X) for tree in self.trees])
        # get prediction for the same sample from all trees for each sample in the test data
        preds = np.swapaxes(predictions, 0, 1)
        #get the most voted value by the trees and store it in the final predictions array
        majority_predictions = np.array([self.most_common_label(pred) for pred in preds])
        return majority_predictions
```

[28]

```python
def accuracy(y_true, y_pred):
    """
    Computes the accuracy of a classification model.

    Parameters:
    y_true (numpy array): A numpy array of true labels for each data point.
    y_pred (numpy array): A numpy array of predicted labels for each data point.

    Returns:
    float: The accuracy of the model, expressed as a percentage.
    """
    y_true = y_true.flatten()
    total_samples = len(y_true)
    correct_predictions = np.sum(y_true == y_pred)
    return (correct_predictions / total_samples)
```

[35]

```python
from sklearn.preprocessing import LabelEncoder

label_encoder = LabelEncoder()
y_train_encoded = label_encoder.fit_transform(y_train)
y_test_encoded = label_encoder.transform(y_test)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_label.py:116: DataConversionWarning:

A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().

/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_label.py:134: DataConversionWarning:

A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
```

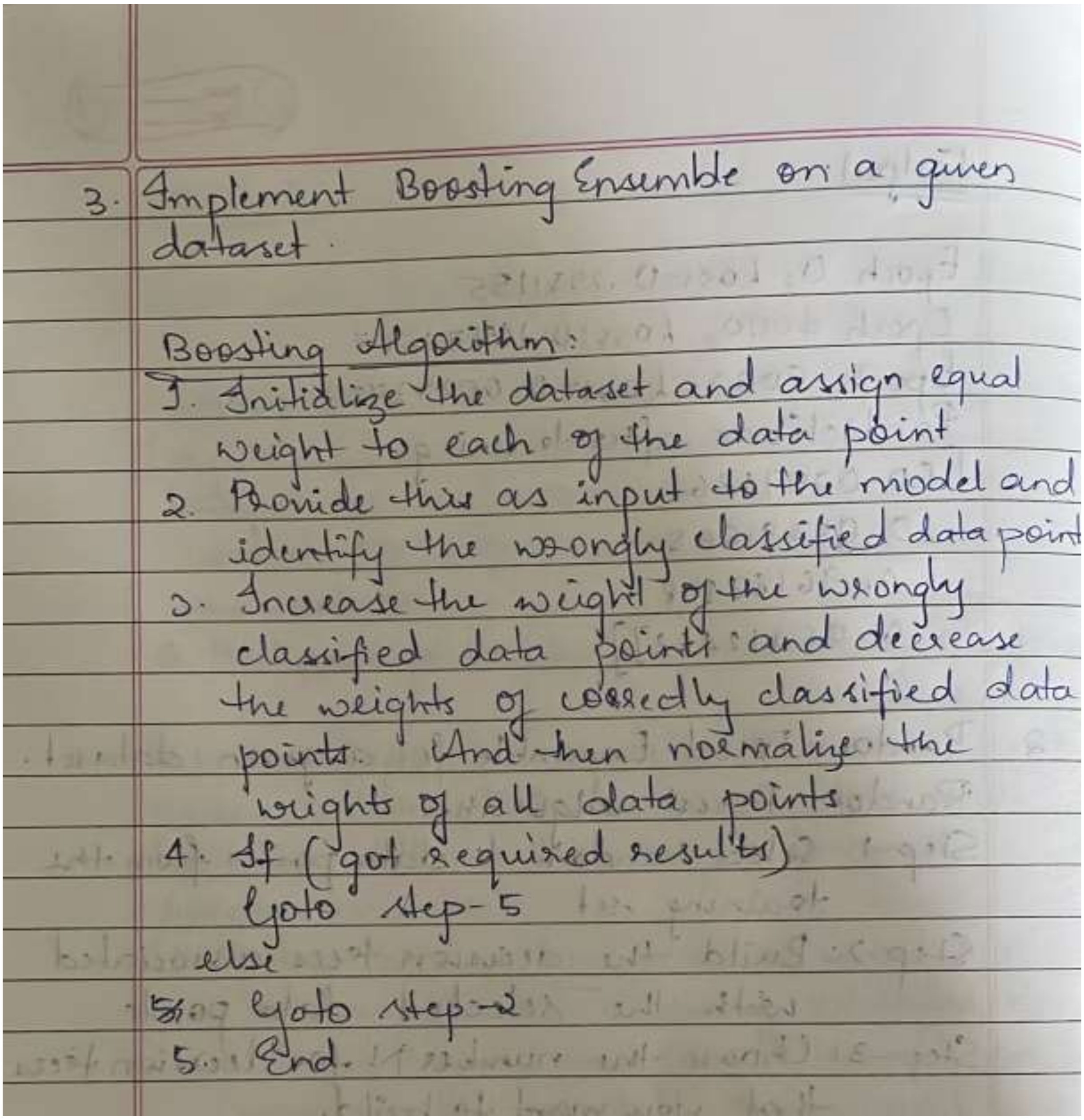
```
[39] from sklearn.preprocessing import LabelEncoder

     label_encoder = LabelEncoder()
     y_train_encoded = label_encoder.fit_transform(y_train.ravel())
     y_test_encoded = label_encoder.transform(y_test.ravel())
     model = RandomForest(10, 10, 2)
     model.fit(X_train, y_train_encoded)

     predictions = model.predict(X_test)
     accuracy(y_test_encoded, predictions)
```

```
0.9333333333333333
```

```
from sklearn.tree import DecisionTreeClassifier

# Create and train the decision tree model
dt = DecisionTreeClassifier()
dt.fit(X_train, y_train_encoded)

# Make predictions on the test data
predictions = dt.predict(X_test)

# Calculate accuracy
accuracy(y_test_encoded, predictions)
```

```
0.9
```

11b.Implement Boosting ensemble method on a given dataset.
Observation Screenshot:



3. Implement Boosting Ensemble on a given dataset.

Boosting Algorithm:

1. Initialize the dataset and assign equal weight to each of the data point
2. Provide this as input to the model and identify the wrongly classified data point
3. Increase the weight of the wrongly classified data points and decrease the weights of correctly classified data points. And then normalize the weights of all data points
4. If (got required results)
   Goto step-5
   else
   Goto step-2
5. End.

Code and output:

```
[15] # Compute error rate, alpha and w
     def compute_error(y, y_pred, w_i):
         '''
         Calculate the error rate of a weak classifier m. Arguments:
         y: actual target value
         y_pred: predicted value by weak classifier
         w_i: individual weights for each observation

         Note that all arrays should be the same length
         '''
         return (sum(w_i * (np.not_equal(y, y_pred)).astype(int)))/sum(w_i)

     def compute_alpha(error):
         '''
         Calculate the weight of a weak classifier m in the majority vote of the final classifier. This is called
         alpha in chapter 10.1 of The Elements of Statistical Learning. Arguments:
         error: error rate from weak classifier m
         '''
         return np.log((1 - error) / error)

     def update_weights(w_i, alpha, y, y_pred):
         '''
         Update individual weights w_i after a boosting iteration. Arguments:
         w_i: individual weights for each observation
         y: actual target value
         y_pred: predicted value by weak classifier
         alpha: weight of weak classifier used to estimate y_pred
         '''
         return w_i * np.exp(alpha * (np.not_equal(y, y_pred)).astype(int))
```

```
[16] # Define AdaBoost class
     class AdaBoost:

         def __init__(self):
             self.alphas = []
             self.G_M = []
             self.M = None
             self.training_errors = []
             self.prediction_errors = []

         def fit(self, X, y, M = 100):
             '''
             Fit model. Arguments:
             X: independent variables - array-like matrix
             y: target variable - array-like vector
             M: number of boosting rounds. Default is 100 - integer
             '''

             # Clear before calling
             self.alphas = []
             self.training_errors = []
             self.M = M

             # Iterate over M weak classifiers
             for m in range(0, M):

                 # Set weights for current boosting iteration
                 if m == 0:
                     w_i = np.ones(len(y)) * 1 / len(y)  # At m = 0, weights are all the same and equal to 1 / N
                 else:
                     # (d) Update w_i
                     w_i = update_weights(w_i, alpha_m, y, y_pred)

                 # (a) Fit weak classifier and predict labels
                 G_m = DecisionTreeClassifier(max_depth = 1)     # Stump: Two terminal-node classification tree
                 G_m.fit(X, y, sample_weight = w_i)
                 y_pred = G_m.predict(X)

                 self.G_M.append(G_m) # Save to list of weak classifiers

                 # (b) Compute error
                 error_m = compute_error(y, y_pred, w_i)
```

```
[ ]                 w_i = update_weights(w_i, alpha_m, y, y_pred)

                 # (a) Fit weak classifier and predict labels
                 G_m = DecisionTreeClassifier(max_depth = 1)     # Stump: Two terminal-node classification tree
                 G_m.fit(X, y, sample_weight = w_i)
                 y_pred = G_m.predict(X)

                 self.G_M.append(G_m) # Save to list of weak classifiers

                 # (b) Compute error
                 error_m = compute_error(y, y_pred, w_i)
                 self.training_errors.append(error_m)

                 # (c) Compute alpha
                 alpha_m = compute_alpha(error_m)
                 self.alphas.append(alpha_m)

             assert len(self.G_M) == len(self.alphas)

         def predict(self, X):
             '''
             Predict using fitted model. Arguments:
             X: independent variables - array-like
             '''

             # Initialise dataframe with weak predictions for each observation
             weak_preds = pd.DataFrame(index = range(len(X)), columns = range(self.M))

             # Predict class label for each weak classifier, weighted by alpha_m
             for m in range(self.M):
                 y_pred_m = self.G_M[m].predict(X) * self.alphas[m]
                 weak_preds.iloc[:,m] = y_pred_m

             # Calculate final predictions
             y_pred = (1 * np.sign(weak_preds.T.sum())).astype(int)

             return y_pred
```

```
[17] import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier

# Dataset
df = pd.read_csv('/content/spambase.data', header = None)

# Column names
names = pd.read_csv('/content/spambase.names', sep = ':', skiprows=range(0, 33), header = None)
col_names = list(names[0])
col_names.append('Spam')

# Rename df columns
df.columns = col_names

# Convert classes in target variable to {-1, 1}
df['Spam'] = df['Spam'] * 2 - 1

# Train - test split
X_train, X_test, y_train, y_test = train_test_split(df.drop(columns = 'Spam').values,
                                                    df['Spam'].values,
                                                    train_size = 3065,
                                                    random_state = 2)
```

```
# Fit model
ab = AdaBoost()
ab.fit(X_train, y_train, M = 400)

# Predict on test set
y_pred = ab.predict(X_test)

from sklearn.metrics import accuracy_score

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.9440104166666666
```