VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
on

Machine Learning (23CS6PCMAL)

Submitted by

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in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING

B.M.S. COLLEGE OF ENGINEERING
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B.M.S. College of Engineering,

Bull Temple Road, Bangalore 560019

(Affiliated To Visvesvaraya Technological University, Belgaum)

Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the Lab work entitled "Machine Learning (23CS6PCMAL)" carried out by **Shreya CY (1BM22CS265),** 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. The Lab report has been approved as it satisfies the academic requirements in respect of an Machine Learning (23CS6PCMAL) work prescribed for the said degree.

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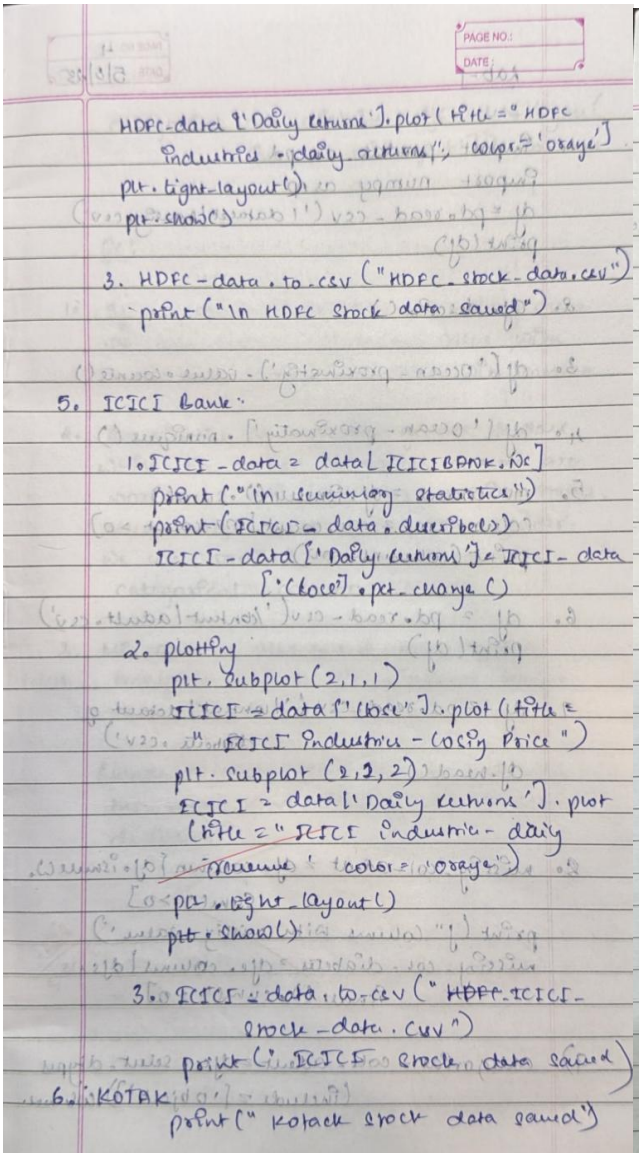
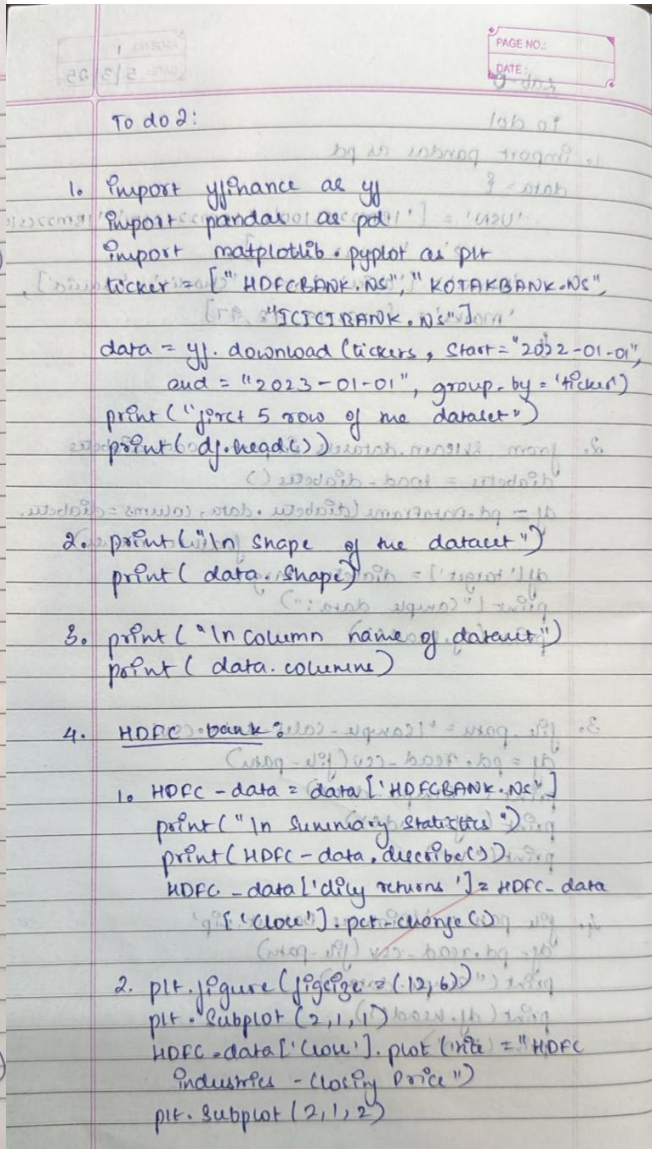
Github Link:
https://github.com/Shreyacy/ML-LABB

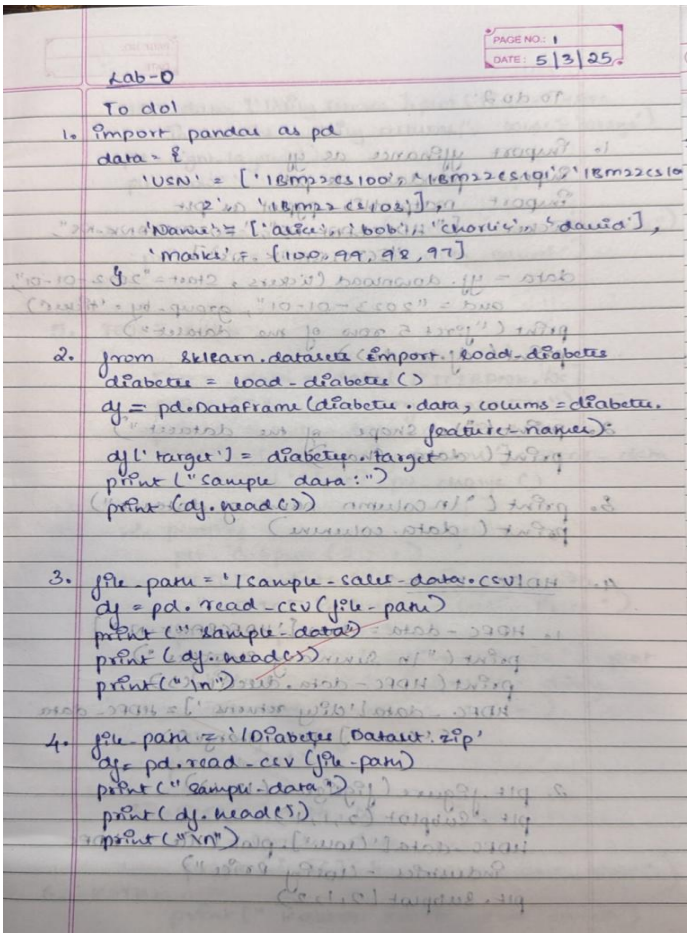
Program 1

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

Screenshot







Code:

```
import pandas as pd
data = {
   'Name': ['Alice', 'Bob', 'Charlie', 'David'],
   'Age': [25, 30, 35, 40],
   'City': ['New York', 'Los Angeles', 'Chicago', 'Houston']
}
df = pd.DataFrame(data)
print("Sample data:")
print(df.head())
```

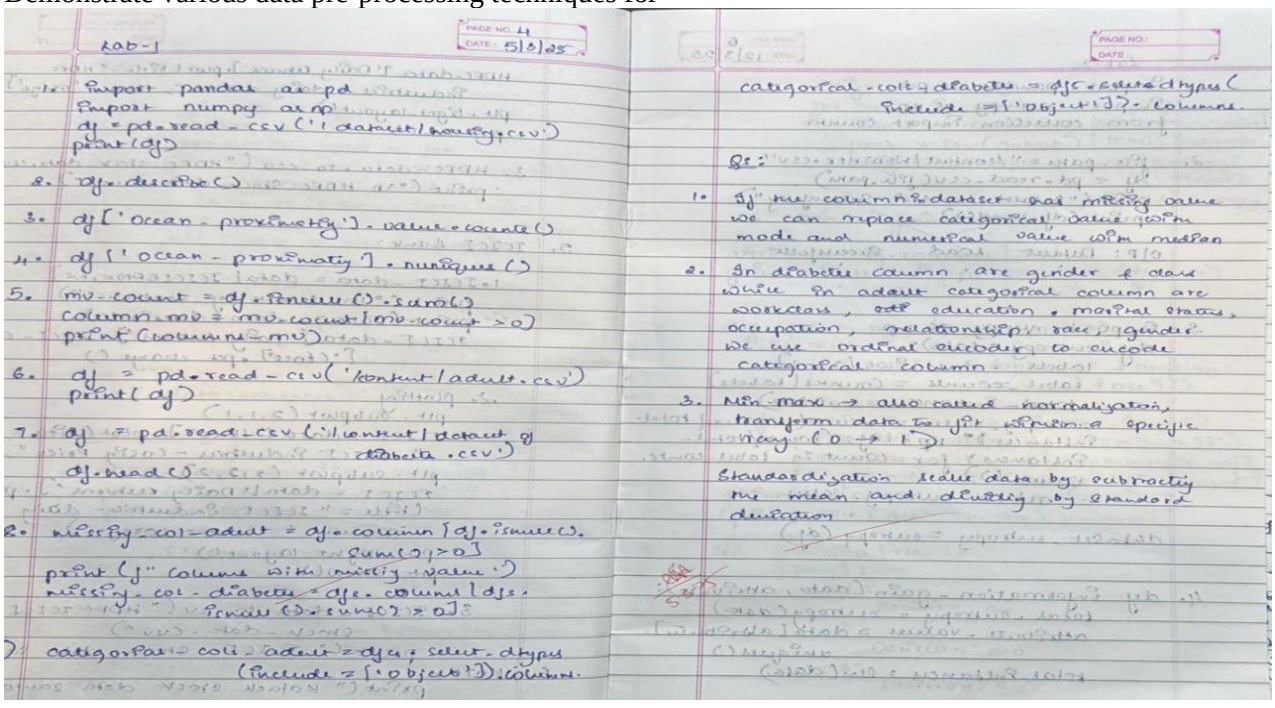
```
import pandas as pd
data={
   'USN':[100,101,102,103],
   'Name':['Alice','Bob','Charlie','David'],
   'Marks':[25,30,35,40],
}
```

```
df=pd.DataFrame(data)
print(df.head())


from sklearn.datasets import load_diabetes
diabetes = load_diabetes()
df = pd.DataFrame(diabetes.data, columns=diabetes.feature_names)
df['target'] = diabetes.target
print("Sample data:")
print(df.head())

file_path = '/content/sample_sales_data.csv'
df = pd.read_csv(file_path)
print("Sample data:")
print(df.head())
print("\n")

df = pd.read_csv('/content/Dataset_of_Diabetes.csv')
print("Sample data:")
print(df.head())


import yfinance as yf
import pandas as pd
import matplotlib.pyplot as plt
tickers = ["HDFCBANK.NS", "ICICIBANK.NS", "KOTAKBANK.NS"]
data = yf.download(tickers, start="2024-01-01", end="2024-12-30", group_by='ticker')

print("First 5 rows of the dataset:")
print(data.head())


hdfc_data=data['HDFCBANK.NS']
icici_data=data['ICICIBANK.NS']
kotak_data=data['KOTAKBANK.NS']

print("\nSummary statistics for Reliance Industries:")
print(hdfc_data.describe())
hdfc_data['Daily Return'] = hdfc_data['Close'].pct_change()
plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
hdfc_data['Close'].plot(title="HDFC - Closing Price")
plt.subplot(2, 1, 2)
hdfc_data['Daily Return'].plot(title="HDFC - Daily Returns", color='orange')
plt.tight_layout()
plt.show()
print("\nSummary statistics for Reliance Industries:")
print(icici_data.describe())
```

```
icici_data['Daily Return'] = icici_data['Close'].pct_change()
plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
icici_data['Close'].plot(title="ICICI - Closing Price")
plt.subplot(2, 1, 2)
icici_data['Daily Return'].plot(title="ICICI - Daily Returns", color='orange')
plt.tight_layout()
plt.show()

print("\nSummary statistics for Reliance Industries:")
print(kotak_data.describe())
kotak_data['Daily Return'] = kotak_data['Close'].pct_change()
plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
kotak_data['Close'].plot(title="kotak - Closing Price")
plt.subplot(2, 1, 2)
kotak_data['Daily Return'].plot(title="kotak - Daily Returns", color='orange')
plt.tight_layout()
plt.show()
```

Program 2

Demonstrate various data pre-processing techniques for



a given dataset

Screenshot

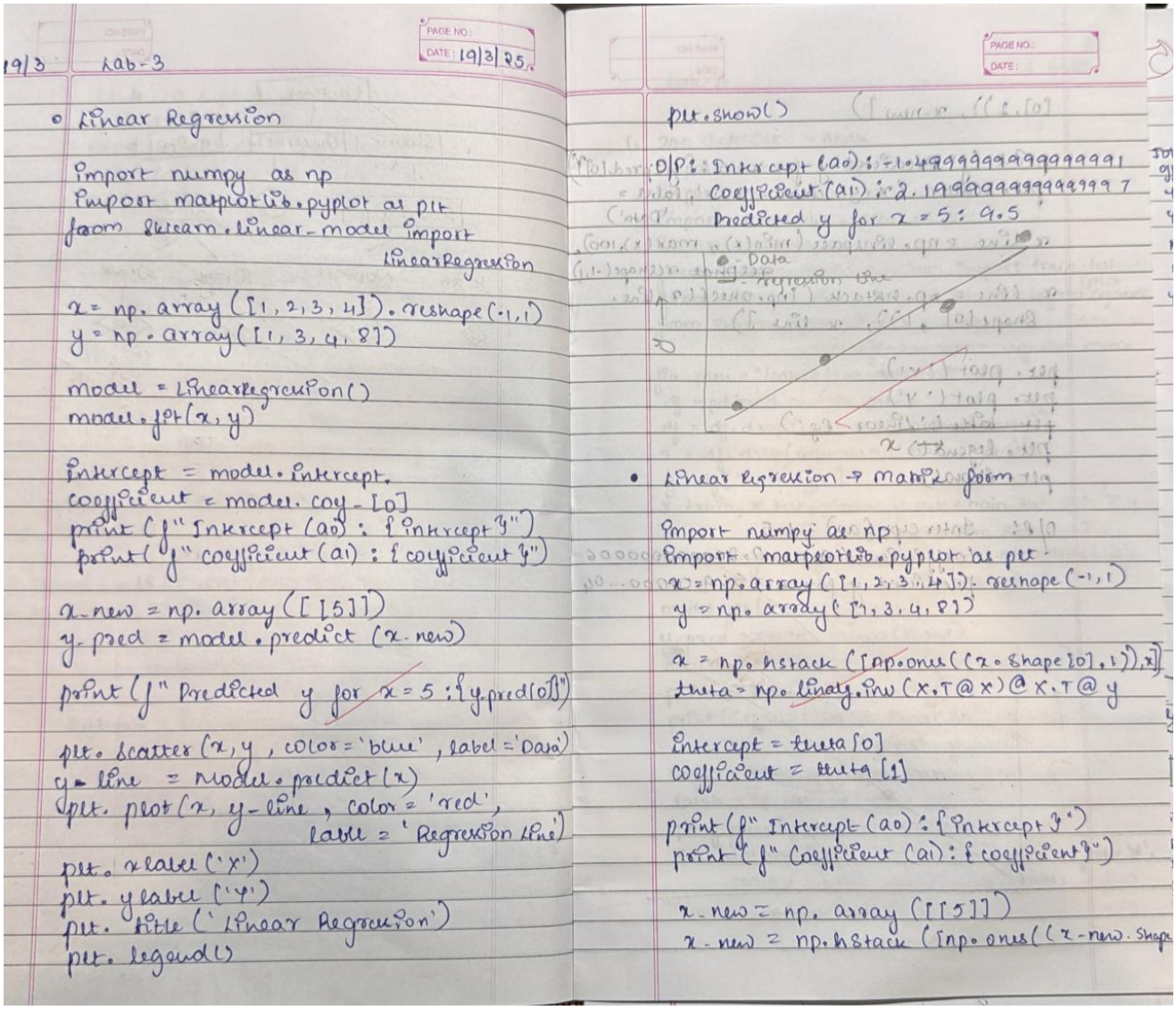
Code:

```
import pandas as pd
import numpy as np
df = pd.read_csv('/content/housing.csv')
print(df)

df.describe()

df['ocean_proximity'].value_counts()

df['ocean_proximity'].nunique()

mv=df.isnull().sum()
cmv=mv[mv>0]
print(cmv)

df4=pd.read_csv('/content/adult.csv')
df4.head()

df5=pd.read_csv('/content/Dataset_of_Diabetes.csv')
df5.head()

missing_cols_adult = df4.columns[df4.isnull().sum() > 0]
print(f"Columns with missing values in 'adult.csv': {missing_cols_adult.tolist()}")
missing_cols_diabetes = df5.columns[df5.isnull().sum() > 0]
print(f"Columns with missing values in 'Dataset of Diabetes .csv': {missing_cols_diabetes.tolist()}")

categorical_cols_adult = df4.select_dtypes(include=['object']).columns
print(f"Categorical columns in 'adult.csv': {categorical_cols_adult.tolist()}")

categorical_cols_diabetes = df5.select_dtypes(include=['object']).columns
print(f"Categorical columns in 'Dataset of Diabetes .csv': {categorical_cols_diabetes.tolist()}")
```

Program 3

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset

Screenshot



19/3 Lab-3

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- Linear Regression

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import
                        LinearRegression

x = np.array([1,2,3,4]).reshape(-1,1)
y = np.array([1,3,4,8])

model = LinearRegression()
model.fit(x,y)

intercept = model.intercept_
coefficient = model.coef_[0]
print(f"Intercept (a0): {intercept}")
print(f"coefficient (a1): {coefficient}")

x_new = np.array([[5]])
y_pred = model.predict(x_new)

print(f"Predicted y for x = 5 : {y_pred[0]}")

plt.scatter(x,y, color='blue', label='Data')
y_line = model.predict(x)
plt.plot(x, y_line, color='red',
                label='Regression Line')
plt.xlabel('X')
plt.ylabel('Y')
plt.title('Linear Regression')
plt.legend()
plt.show()
```

O/P: Intercept (a0): -1.4999999999999991
Coefficient (a1): 2.1999999999999997
Predicted y for x = 5: 9.5

- Linear Regression - Matrix form

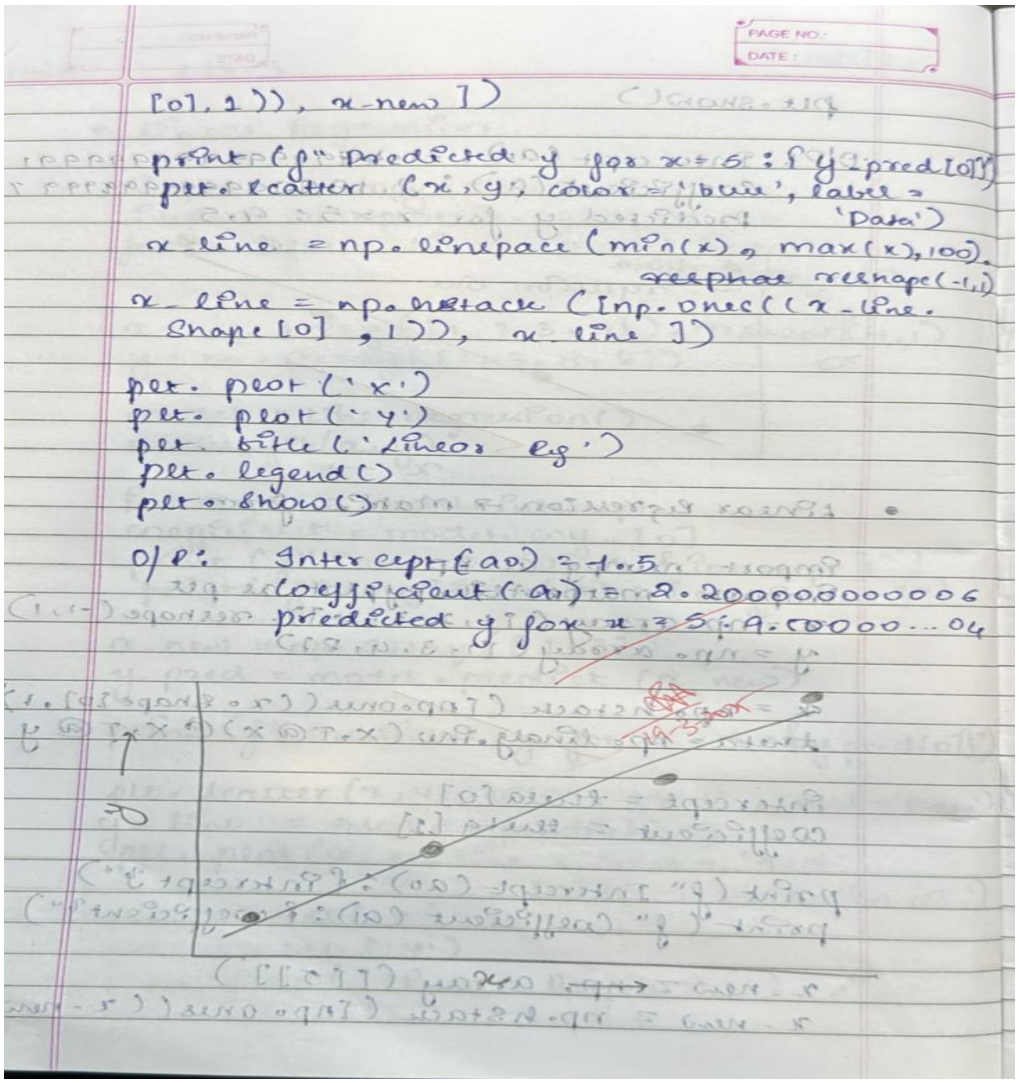
```
import numpy as np
import matplotlib.pyplot as plt
x = np.array([1,2,3,4]).reshape(-1,1)
y = np.array([1,3,4,8])

x = np.hstack([np.ones((x.shape[0],1)),x])
theta = np.linalg.inv(x.T@x)@x.T@y

intercept = theta[0]
coefficient = theta[1]

print(f"Intercept (a0): {intercept}")
print(f"Coefficient (a1): {coefficient}")

x_new = np.array([[5]])
x_new = np.hstack([np.ones((x_new.shape
```



Code:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
x = np.array([1, 2, 3, 4]).reshape(-1, 1)
y = np.array([1, 3, 4, 8])
```

```
model = LinearRegression()
model.fit(x, y)
intercept = model.intercept_
coefficient = model.coef_[0]
print(f"Intercept (a0): {intercept}")
print(f"Coefficient (a1): {coefficient}")
x_new = np.array([[5]])
y_pred = model.predict(x_new)
print(f"Predicted y for x=5: {y_pred[0]}")
plt.scatter(x, y, color='blue', label='Data')
y_line = model.predict(x)
plt.plot(x, y_line, color='red', label='Regression Line')
plt.xlabel('X')
plt.ylabel('Y')
plt.title('Linear Regression')
plt.legend()
plt.show()
```

```
import numpy as np
import matplotlib.pyplot as plt
x = np.array([1, 2, 3, 4]).reshape(-1, 1)
y = np.array([1, 3, 4, 8])
X = np.hstack([np.ones((x.shape[0], 1)), x])
theta = np.linalg.inv(X.T @ X) @ X.T @ y
intercept = theta[0]
coefficient = theta[1]
print(f"Intercept (a0): {intercept}")
print(f"Coefficient (a1): {coefficient}")
x_new = np.array([[5]])
X_new = np.hstack([np.ones((x_new.shape[0], 1)), x_new])
y_pred = X_new @ theta

print(f"Predicted y for x=5: {y_pred[0]}")
plt.scatter(x, y, color='blue', label='Data')
x_line = np.linspace(min(x), max(x), 100).reshape(-1, 1)
X_line = np.hstack([np.ones((x_line.shape[0], 1)), x_line])
y_line = X_line @ theta

plt.plot(x_line, y_line, color='red', label='Regression Line')
plt.xlabel('X')
plt.ylabel('Y')
plt.title('Linear Regression')
plt.legend()
plt.show()
```

Program 4

Build Logistic Regression Model for a given dataset

Screenshot

1. For dataset file "HR-comma-sep.csv"

i) i. Key factors like satisfaction level, last evaluation, avg monthly hrs, time spent and salary level

ii. Employee with low satisfaction & high working level has tend to leave more

iii. Salary impacts retention as employees with low salaries are more likely to leave.

ii) Model Accuracy:
→ The logistic model accuracy depends on dataset & split
→ If accuracy is above 80% it good
→ Too low: 50-60%

2. For goo dataset
i. Data Preprocessing:
- dropped the animal-name column, as it is not input feature
- converted categorical labels to numerical for model training

ii. Handling Inconsistent value
- check for missing value, either remove or fill using mean/mode value

iii. Insights from confusion matrix:
- It shows how well model classified different animal type
- Diagonal value indicate correct prediction

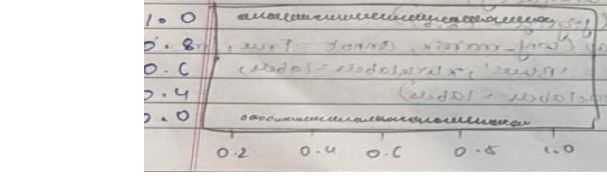
iv: most misclassified class type:
- Some animals with similar characteristics might have been misclassified
- Misclassification occurs when two classes share common features, making sep difficult

	Precision	recall	f1 score	support
1	1.00	1.00	1.00	12
2	1.00	1.00	1.00	8
3	0.00	0.00	0.00	0
4	0.67	1.00	0.80	2
5	1.00	1.00	1.00	3
6	1.00	1.00	1.00	1
accuracy			0.95	21
macro avg	0.78	0.83	0.80	21
weighted avg	0.92	0.95	0.93	21

1	12	0	0	0	0	0
2	0	2	0	0	0	0
3	0	0	0	1	0	0
4	0	0	0	2	0	0
5	0	0	0	0	3	0
6	0	0	0	0	0	1

1 2 3 4 5 6

2. HR
O/P: Probability of leaving: 0.41
The employee will stay



1. Consider a binary classification problem where we want to predict whether a student will pass or fail. $a_0 = 5$ $a_1 = 0.8$.

a) $\frac{1}{1+e^{(-z)}}$

$z = a_0 + a_1 x$

b) $\frac{1}{1+e^{-(5+0.8)}} = 0.6457 = 64.57\%$

c) 0.65 is pass

2. Consider $z = [2, 1, 0]$.

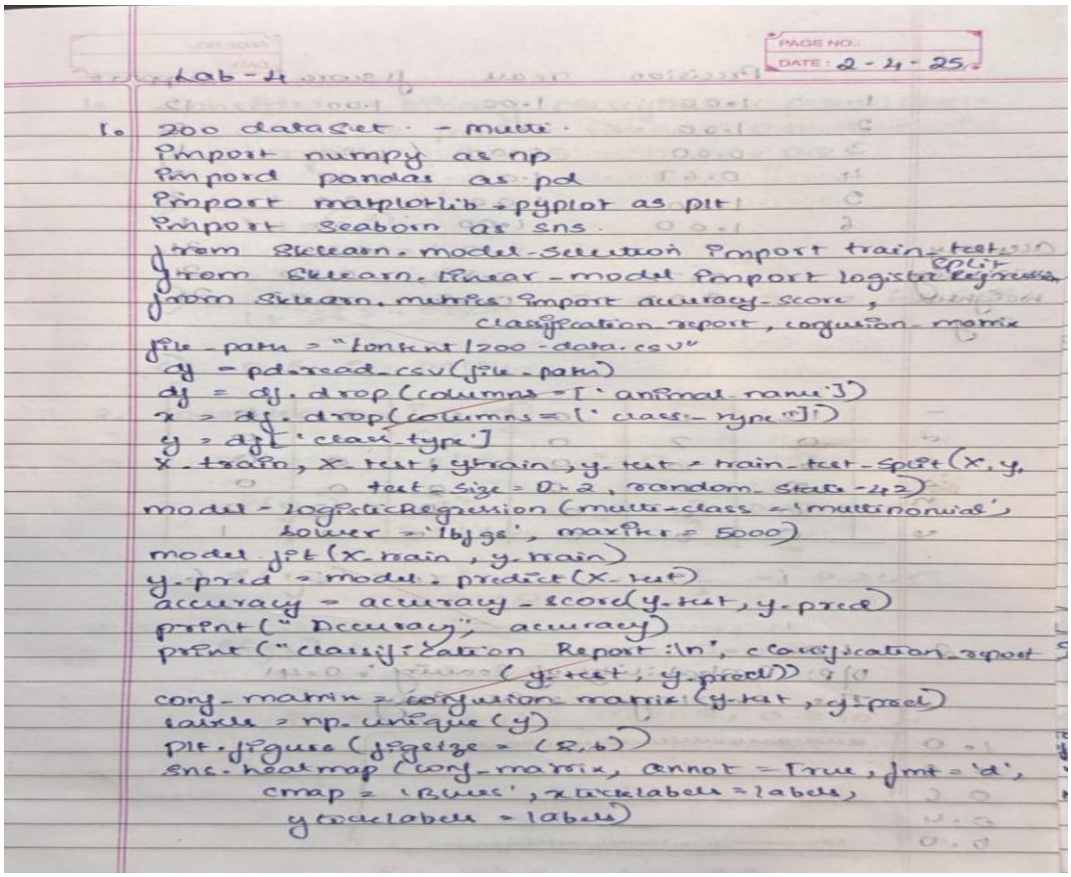
$e^2 = 7.39$, $e^1 = 2.71$, $e^0 = 1$

$P(y_1) = \frac{e^2}{2+1+0} \Rightarrow \frac{2}{3} \Rightarrow 0.665$

$P(y_2) = \frac{e^1}{2+1+0} \Rightarrow \frac{1}{3} \Rightarrow 0.245$

$P(y_3) = \frac{e^0}{2+1+0} = 0.090$

$P_3 = [0.665, 0.245, 0.090]$.



Code:

```
import pandas as pd
from matplotlib import pyplot as plt
import math
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression

# Load HR dataset
df = pd.read_csv("/content/HR_comma_sep (1).csv")
df.head()

plt.scatter(df.satisfaction_level, df.left, marker='+', color='red')

# Splitting dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(df[['satisfaction_level']], df.left, train_size=0.9,
random_state=10)
X_train.shape

X_test

# Training logistic regression model
model = LogisticRegression()
model.fit(X_train, y_train)
```

```
X_test
y_test
y_predicted = model.predict(X_test)
y_predicted

model.score(X_test, y_test)

model.predict_proba(X_test)

y_predicted = model.predict([[0.5]])

# model.coef_ indicates value of m in y=m*x + b equation
model.coef_

# model.intercept_ indicates value of b in y=m*x + b equation
model.intercept_

# Define sigmoid function and do the math manually
def sigmoid(x):
    return 1 / (1 + math.exp(-x))

def prediction_function(satisfaction_level):
    z = model.coef_[0][0] * satisfaction_level + model.intercept_[0]
    y = sigmoid(z)
    return y

satisfaction_level = 0.35
probability = prediction_function(satisfaction_level)
print(f"Probability of leaving: {probability:.2f}")

if probability >= 0.5:
    print("The employee will leave.")
else:
    print("The employee will stay.")


import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Load dataset
file_path = "/content/zoo-data (1).csv"
df = pd.read_csv(file_path)

# Drop the animal_name column as it is not a feature
df = df.drop(columns=["animal_name"])

# Define features and target
```

```
X = df.drop(columns=["class_type"])
y = df["class_type"]

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train multinomial logistic regression model
model = LogisticRegression(multi_class='multinomial', solver='lbfgs', max_iter=500)
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

# Evaluate model
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
print("Classification Report:\n", classification_report(y_test, y_pred))

# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
labels = np.unique(y)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=labels, yticklabels=labels)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```

Program 5

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

Screenshot

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Lab-2

1. import pandas as pd
import numpy as np
from collection import Counter

2. file_path = "/content/WEATHER.CSV"
df = pd.read_csv(file_path)
print("Dataset loaded successfully")
print(df.head())

O/P: Dataset load succesfull

3. import numpy as np
def entropy(data):
labels = data.iloc[:,-1]
label_counts = Counter(labels)
total_instances = len(data)
entropy_value = -sum((count/total_instances) * np.log2(count/total_instances) for count in label_counts.values())
return entropy_value

dataset_entropy = entropy(df)

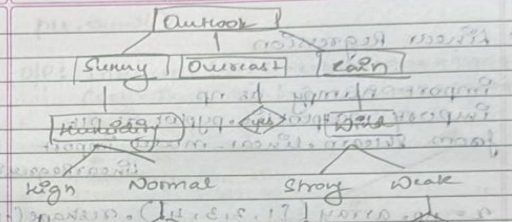
4. def information_gain(data, attribute):
total_entropy = entropy(data)
attribute_values = data[attribute].unique()
total_instances = len(data)
weighted_entropy = 0
for value in attribute_values:
subset = data[data[attribute] == value]
prob = len(subset) / total_instances
weighted_entropy += prob * entropy(subset)
gain = total_entropy - weighted_entropy
return gain

attributes = df.columns[:-1]
gains = {attr: information_gain(df, attr) for attr in attributes}

def print_tree(tree, depth=0):
if not isinstance(tree, dict):
print(" " * depth + f"-> Decision: {tree}")
return
for attribute, branches in tree.items():
print(" " * depth + f"[{attribute}]")
for value, subtree in branches.items():
print(" " * (depth+1) + f"-> {value}:")
print_tree(subtree, depth+2)
print("\nDecision Tree (row-wise):")
print_tree(decision_tree)

O/P: Decision Tree ()
[Day]:
1:
Decision: No
2:
Decision: No
3:
Decision: Yes
4:
Decision: Yes
5:
Decision: Yes
6:
Decision: No
7:
Decision: Yes
8:
Decision: No
9:
Decision: Yes
10:
Decision: Yes
11:
Decision: Yes
12:
Decision: Yes
13:
Decision: Yes
14:
Decision: No

{outlook: {'Sunny': {humidity: {'high': 'no', 'normal': 'yes'}}, 'Overcast': 'yes', 'rainy': {'windy': {'weak': 'yes', 'strong': 'no'}}}}



Code:

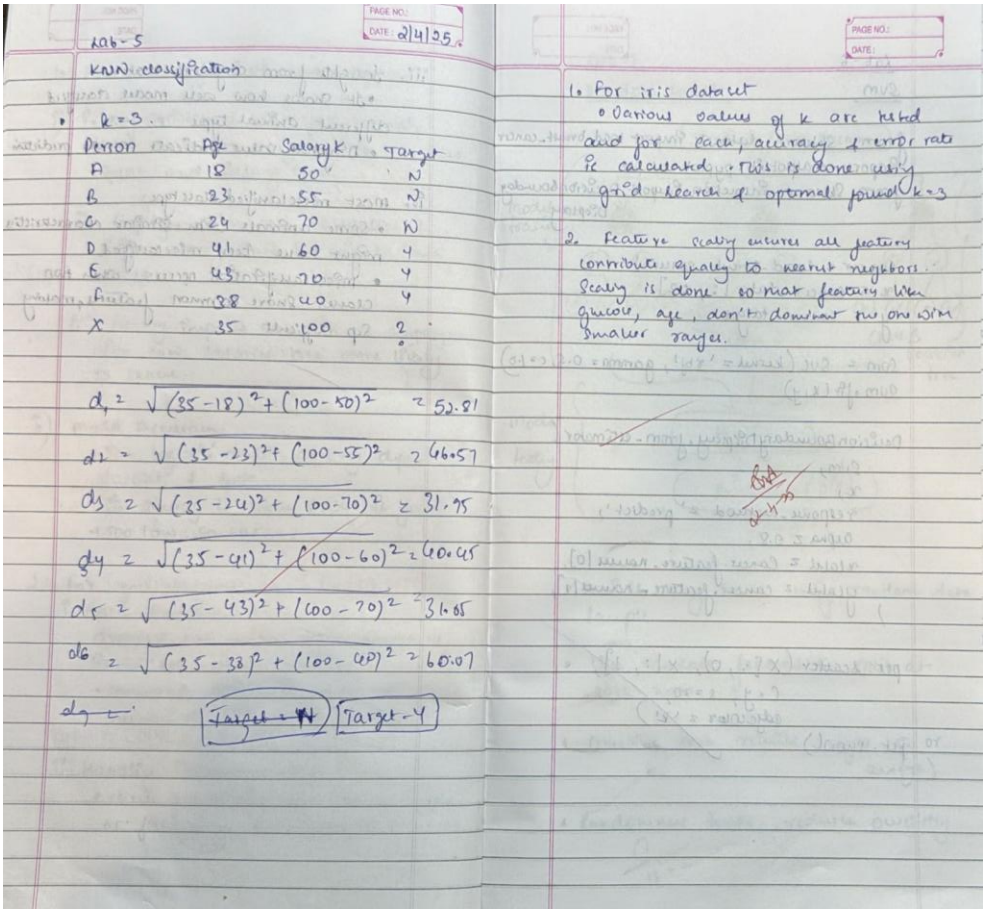
```
import numpy as np
import pandas as pd
from collections import Counter

class Node:
    def __init__(self, feature=None, value=None, label=None):
        self.feature = feature
        self.value = value
        self.label = label
        self.children = {}

def entropy(y):
    counts = np.bincount(y)
    probabilities = counts / len(y)
    return -np.sum([p * np.log2(p) for p in probabilities if p > 0])

def information_gain(X, y, feature):
    total_entropy = entropy(y)
    values, counts = np.unique(X[:, feature], return_counts=True)
    weighted_entropy = sum((counts[i] / sum(counts)) * entropy(y[X[:, feature] == v]) for i, v in
enumerate(values))
    return total_entropy - weighted_entropy

def best_feature_to_split(X, y):
    gains = [information_gain(X, y, i) for i in range(X.shape[1])]
    return np.argmax(gains)

def id3(X, y, features):
    if len(set(y)) == 1:
        return Node(label=y[0])
    if len(features) == 0:
        return Node(label=Counter(y).most_common(1)[0][0])
    best_feature = best_feature_to_split(X, y)
    node = Node(feature=features[best_feature])
    feature_values = np.unique(X[:, best_feature])
    for value in feature_values:
        sub_X = X[X[:, best_feature] == value]
        sub_y = y[X[:, best_feature] == value]
        if len(sub_y) == 0:
            node.children[value] = Node(label=Counter(y).most_common(1)[0][0])
        else:
            node.children[value] = id3(np.delete(sub_X, best_feature, axis=1), sub_y, features[:best_feature] +
features[best_feature+1:])
    return node

def print_tree(node, depth=0):
    if node.label is not None:
        print(f"{' ' * depth}Leaf: {node.label}")
        return
    print(f"{' ' * depth}Feature: {node.feature}")
    for value, child in node.children.items():
```

```
        print(f"{'  ' * depth}Value: {value}")
        print_tree(child, depth + 1)

data = pd.DataFrame({
    'Outlook': ['Sunny', 'Sunny', 'Overcast', 'Rain', 'Rain', 'Rain', 'Overcast', 'Sunny', 'Sunny', 'Rain', 'Sunny',
'Overcast', 'Overcast', 'Rain'],
    'Temperature': ['Hot', 'Hot', 'Hot', 'Mild', 'Cool', 'Cool', 'Cool', 'Mild', 'Cool', 'Mild', 'Mild', 'Mild', 'Hot', 'Mild'],
    'Humidity': ['High', 'High', 'High', 'High', 'Normal', 'Normal', 'Normal', 'High', 'Normal', 'Normal', 'Normal',
'High', 'Normal', 'High'],
    'Wind': ['Weak', 'Strong', 'Weak', 'Weak', 'Weak', 'Strong', 'Strong', 'Weak', 'Weak', 'Weak', 'Strong', 'Strong',
'Weak', 'Strong'],
    'PlayTennis': ['No', 'No', 'Yes', 'Yes', 'Yes', 'No', 'Yes', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'No']
})


X = data.iloc[:, :-1].apply(lambda col: pd.factorize(col)[0]).to_numpy()
y = pd.factorize(data['PlayTennis'])[0]
features = list(data.columns[:-1])

decision_tree = id3(X, y, features)
print_tree(decision_tree)
```

Program 6

Build KNN Classification model for a given dataset

Screenshot



Code:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

# Load the dataset
iris = pd.read_csv("/content/iris (2).csv")

# Split features and labels
X = iris.iloc[:, :-1]  # Features: all columns except last
y = iris.iloc[:, -1]   # Labels: last column (species)

# Split into training (80%) and testing (20%) sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# Initialize and train the KNN model
k = 5  # Choosing k=5
knn = KNeighborsClassifier(n_neighbors=k)
knn.fit(X_train, y_train)

# Make predictions
y_pred = knn.predict(X_test)

# Evaluate the model
print("Accuracy Score:", accuracy_score(y_test, y_pred))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))

# Plot confusion matrix
plt.figure(figsize=(6, 5))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, cmap="Blues", fmt="d",
            xticklabels=knn.classes_, yticklabels=knn.classes_)
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix - Iris Dataset")
plt.show()
```

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

# Load the dataset
diabetes = pd.read_csv("/content/diabetes (1).csv")

# Split features and labels
X = diabetes.iloc[:, :-1]  # Features: all columns except last
y = diabetes.iloc[:, -1]   # Labels: last column (diabetic or not)

# Split into training (80%) and testing (20%) sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Feature scaling (important for KNN)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Initialize and train the KNN model
k = 5  # Choosing k=5
```

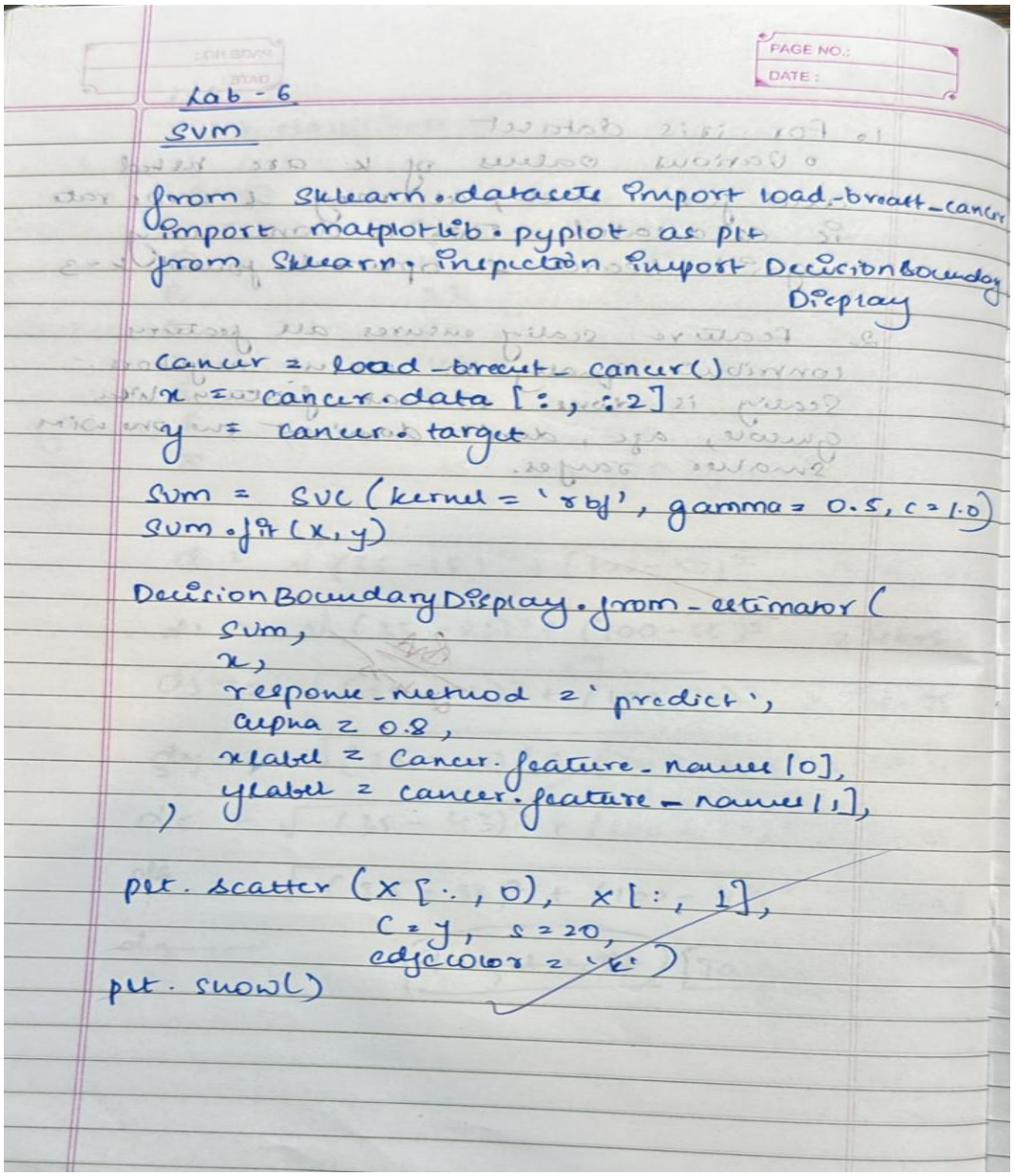
```
knn = KNeighborsClassifier(n_neighbors=k)
knn.fit(X_train, y_train)

# Make predictions
y_pred = knn.predict(X_test)

# Evaluate the model
print("Accuracy Score:", accuracy_score(y_test, y_pred))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))

# Plot confusion matrix
plt.figure(figsize=(6, 5))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, cmap="Blues", fmt="d",
            xticklabels=["Non-Diabetic", "Diabetic"], yticklabels=["Non-Diabetic", "Diabetic"])
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix - Diabetes Dataset")
plt.show()


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

# Load dataset
df = pd.read_csv('/content/heart (1).csv')

# Define features and target
X = df.drop(columns=['target'])  # Assuming 'target' is the classification column
y = df['target']

# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Feature scaling
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Find the best K value
k_values = range(1, 21)
accuracy_scores = []
for k in k_values:
    model = KNeighborsClassifier(n_neighbors=k)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy_scores.append(accuracy_score(y_test, y_pred))
```

```
best_k = k_values[np.argmax(accuracy_scores)]
print(f'Best K value: {best_k}')

# Train model with best K
best_model = KNeighborsClassifier(n_neighbors=best_k)
best_model.fit(X_train, y_train)
y_pred = best_model.predict(X_test)

# Evaluate model
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy with best K ({best_k}): {accuracy:.4f}')
print("Classification Report:")
print(classification_report(y_test, y_pred))

# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title(f'Confusion Matrix - KNN (K={best_k})')
plt.show()

# Plot K values vs. Accuracy
plt.plot(k_values, accuracy_scores, marker='o')
plt.xlabel('K Value')
plt.ylabel('Accuracy')
plt.title('K Value vs Accuracy')
plt.show()
```

Program 7

Build Support vector machine model for a given dataset

Screenshot



Lab - 6

SVM

```
from sklearn.datasets import load_breast_cancer
import matplotlib.pyplot as plt
from sklearn.inspection import DecisionBoundaryDisplay

cancer = load_breast_cancer()
X = cancer.data[:, :2]
y = cancer.target

svm = SVC(kernel='rbf', gamma=0.5, C=1.0)
svm.fit(X, y)

DecisionBoundaryDisplay.from_estimator(
    svm,
    X,
    response_method='predict',
    alpha=0.8,
    xlabel=cancer.feature_names[0],
    ylabel=cancer.feature_names[1],
)

plt.scatter(X[:, 0], X[:, 1],
            c=y, s=20,
            edgecolor='k')
plt.show()
```

Code:

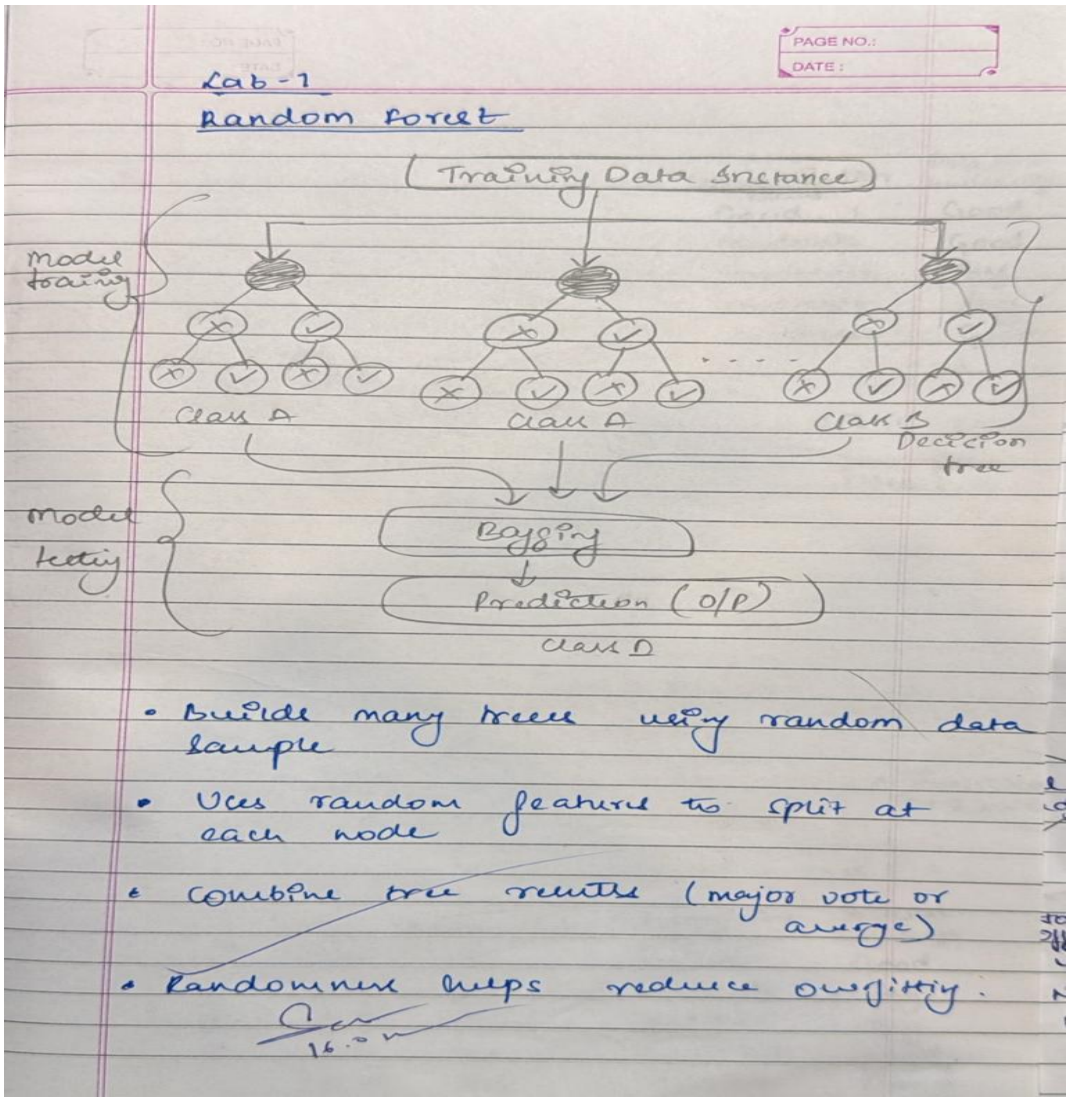
 # Load the important packages

```
from sklearn.datasets import load_breast_cancer
import matplotlib.pyplot as plt
from sklearn.inspection import DecisionBoundaryDisplay
from sklearn.svm import SVC

# Load the datasets
cancer = load_breast_cancer()
X = cancer.data[:, :2]
y = cancer.target

#Build the model
svm = SVC(kernel="rbf", gamma=0.5, C=1.0)
# Trained the model
svm.fit(X, y)

# Plot Decision Boundary
DecisionBoundaryDisplay.from_estimator(
        svm,
        X,
        response_method="predict",
        cmap=plt.cm.Spectral,
        alpha=0.8,
        xlabel=cancer.feature_names[0],
        ylabel=cancer.feature_names[1],
    )

# Scatter plot
plt.scatter(X[:, 0], X[:, 1],
            c=y,
            s=20, edgecolors="k")
plt.show()
```

Program 8

Implement Random forest ensemble method on a given dataset

Screenshot



Code:

```
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix

# Load the iris dataset
iris = load_iris()

# Convert to DataFrame
df = pd.DataFrame(data=iris.data, columns=iris.feature_names)
df['species'] = iris.target
```

```
# Split features and target
X = df.drop('species', axis=1)
y = df['species']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

best_score = 0
best_n = 0
best_cm = None

# Try different numbers of trees
for n in range(1, 101):
    clf = RandomForestClassifier(n_estimators=n, random_state=42)
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    if acc > best_score:
        best_score = acc
        best_n = n
        best_cm = confusion_matrix(y_test, y_pred)

print(f"Best Accuracy: {best_score}")
print(f"Number of Trees: {best_n}")
print("Confusion Matrix:")
print(best_cm)
```

Program 9

Implement Boosting ensemble method on a given dataset

Screenshot

Lab-8 - AdaBoost Algorithm.

3.

CGPA	Interactiveness	Practical knowledge	Communication skills	Job Profile
≥9	Yes	Good	Good	Yes
<9	No	Good	Moderate	Yes
≥9	No	Avg	Moderate	No
<9	No	Avg	Good	No
≥9	Yes	Good	Moderate	Yes
≥9	Yes	Good	Moderate	Yes

CGPA	Predicted job offer	Actual Job offer	Weight
≥9	Yes	Yes	1/6
<9	No	Yes	1/6
≥9	Yes	No	1/6
<9	No	No	1/6
≥9	Yes	Yes	1/6
≥9	Yes	Yes	1/6

$$\varepsilon_{CGPA} = 2 * \frac{1}{6} = 0.333$$

$$\alpha_{CGPA} = \frac{1}{2} \frac{\ln(1 - \varepsilon_{CGPA})}{\varepsilon_{CGPA}}$$

$$= \frac{1}{2} \frac{\ln(1 - 0.333)}{(0.333)} \Rightarrow 0.347.$$

$$Z_{CGPA} = \frac{1}{6} * 4 * e^{-0.347} + \frac{1}{6} * 2 * e^{0.347}$$

$$Z \Rightarrow 0.9428.$$

Weight of correct instance: $\frac{1/6 * e^{-0.347}}{0.9428}$

$$= 0.1249.$$

CGPA	Predicted Job offer	Actual Job offer	Weight
≥9	Yes	Yes	0.1249
<9	No	Yes	0.2501
≥9	Yes	No	0.2501
<9	No	No	0.1249
≥9	Yes	Yes	0.1249
≥9	Yes	Yes	0.1249.

- Insurance oso fpb.

Default Accuracy: 0.8182

Confusion Matrix

[[6782 633
 1144 1211]]

Code:

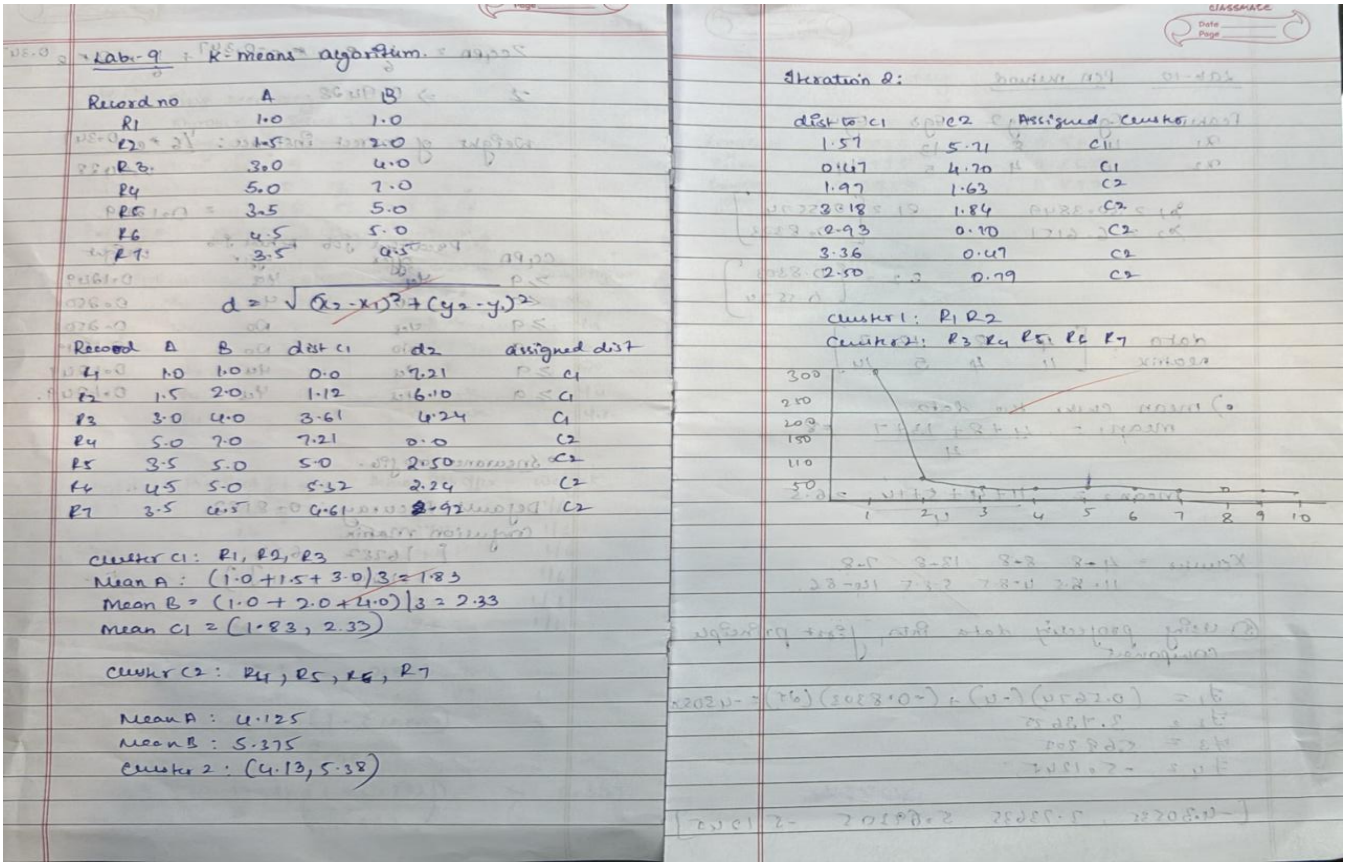
```
import pandas as pd
from sklearn.ensemble import AdaBoostClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt

# Load the dataset
df = pd.read_csv("/content/income (1).csv")

# Encode categorical variables (if any)
label_encoders = {}
for column in df.select_dtypes(include='object').columns:
    le = LabelEncoder()
    df[column] = le.fit_transform(df[column])
    label_encoders[column] = le

# Split dataset into features and target
X = df.drop("income_level", axis=1)  # replace 'income' with the actual target column name if different
y = df["income_level"]

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train AdaBoost with default n_estimators=10
ada_default = AdaBoostClassifier(n_estimators=10, random_state=42)
ada_default.fit(X_train, y_train)
y_pred_default = ada_default.predict(X_test)
default_accuracy = accuracy_score(y_test, y_pred_default)

print(f"Default Accuracy (10 estimators): {default_accuracy:.4f}")
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_default))

# Tune number of estimators
scores = []
n_estimators_range = range(1, 101)

for n in n_estimators_range:
```

```
    ada = AdaBoostClassifier(n_estimators=n, random_state=42)
    ada.fit(X_train, y_train)
    y_pred = ada.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    scores.append(acc)

# Best accuracy and corresponding n_estimators
best_score = max(scores)
best_n_estimators = n_estimators_range[scores.index(best_score)]

# Final model with best n_estimators
ada_best = AdaBoostClassifier(n_estimators=best_n_estimators, random_state=42)
ada_best.fit(X_train, y_train)
y_pred_best = ada_best.predict(X_test)
conf_matrix_best = confusion_matrix(y_test, y_pred_best)

print(f"\nBest Accuracy: {best_score:.4f} using {best_n_estimators} estimators")
print("Best Confusion Matrix:")
print(conf_matrix_best)

# Optional: Plot accuracy vs number of estimators
plt.figure(figsize=(10, 6))
plt.plot(n_estimators_range, scores, marker='o')
plt.title("AdaBoost Accuracy vs Number of Estimators")
plt.xlabel("Number of Estimators")
plt.ylabel("Accuracy")
plt.grid(True)
plt.show()
```

Program 10

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

Screenshot



Lab-9 : K-means algorithm.

Record no	A	B
R1	1.0	1.0
R2	1.5	2.0
R3	3.0	4.0
R4	5.0	7.0
R5	3.5	5.0
R6	4.5	5.0
R7	3.5	4.5

$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$

Record	A	B	dist C1	d2	assigned dist
R1	1.0	1.0	0.0	7.21	C1
R2	1.5	2.0	1.12	6.10	C1
R3	3.0	4.0	3.61	6.24	C1
R4	5.0	7.0	7.21	0.0	C2
R5	3.5	5.0	5.0	2.50	C2
R6	4.5	5.0	5.32	2.24	C2
R7	3.5	4.5	4.61	2.92	C2

Cluster C1: R1, R2, R3
Mean A: (1.0 + 1.5 + 3.0)/3 = 1.83
Mean B = (1.0 + 2.0 + 4.0)/3 = 2.33
Mean C1 = (1.83, 2.33)

Cluster C2: R4, R5, R6, R7

Mean A: 4.125
Mean B: 5.375
Cluster 2: (4.13, 5.38)

Iteration 2:

dist to C1	dist to C2	Assigned Cluster
1.57	5.71	C1
0.47	4.70	C1
1.97	1.63	C2
3.18	1.84	C2
2.93	0.70	C2
3.36	0.47	C2
2.50	0.79	C2

Cluster 1: R1 R2
Cluster 2: R3 R4 R5 R6 R7

Code:

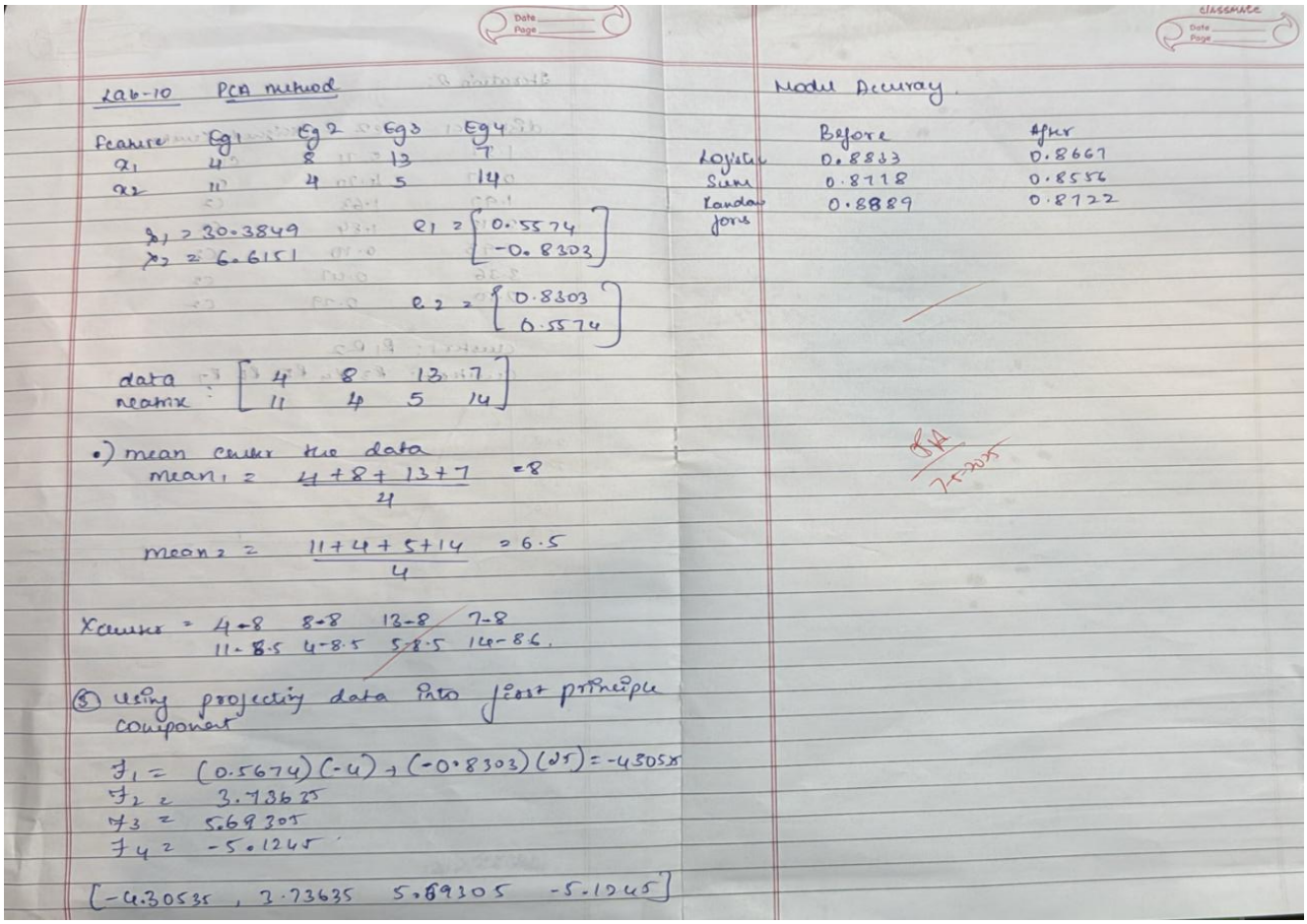
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
```

```
# Load the Iris dataset
iris = load_iris()
df = pd.DataFrame(iris.data, columns=iris.feature_names)
df['target'] = iris.target
# Select only petal length and width
X = df[['petal length (cm)', 'petal width (cm)']]
# Optional: Scale the features (important for distance-based algorithms like K-Means)
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
# Elbow method to determine optimal number of clusters
inertia = []
k_range = range(1, 11)

for k in k_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_scaled)
    inertia.append(kmeans.inertia_)

# Plot the elbow curve
plt.figure(figsize=(8, 5))
plt.plot(k_range, inertia, marker='o')
plt.title('Elbow Method for Optimal k')
plt.xlabel('Number of clusters (k)')
plt.ylabel('Inertia')
plt.grid(True)
plt.show()
# From the elbow plot, we choose k = 3 (typical for Iris dataset)
optimal_k = 3
kmeans_final = KMeans(n_clusters=optimal_k, random_state=42)
clusters = kmeans_final.fit_predict(X_scaled)

# Add cluster labels to original data
df['Cluster'] = clusters

# Plotting the clusters
plt.figure(figsize=(8, 5))
plt.scatter(X_scaled[:, 0], X_scaled[:, 1], c=clusters, cmap='viridis', s=50)
plt.scatter(kmeans_final.cluster_centers_[:, 0], kmeans_final.cluster_centers_[:, 1],
            c='red', s=200, alpha=0.7, marker='X', label='Centroids')
plt.title('K-Means Clustering (k=3) on Iris Petal Features')
plt.xlabel('Petal Length (scaled)')
plt.ylabel('Petal Width (scaled)')
plt.legend()
plt.grid(True)
plt.show()
```

Program 11

Implement Dimensionality reduction using Principal Component Analysis (PCA) method

Screenshot



Code:

```
import pandas as pd
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.decomposition import PCA
from sklearn.metrics import accuracy_score

# Load dataset
df = pd.read_csv("/content/heart (2).csv")  # Update to match your file path if needed

# Define features and target
X = df.drop('HeartDisease', axis=1)
y = df['HeartDisease']

# Identify categorical columns
categorical_cols = X.select_dtypes(include=['object']).columns.tolist()

# Encode categorical columns
for col in categorical_cols:
```

```
    if X[col].nunique() == 2:
        X[col] = LabelEncoder().fit_transform(X[col])
    else:
        X = pd.get_dummies(X, columns=[col])

# Scale features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)

# Initialize models
models = {
    'SVM': SVC(),
    'Logistic Regression': LogisticRegression(max_iter=1000),
    'Random Forest': RandomForestClassifier()
}

# Train and evaluate models (without PCA)
print("🔍 Accuracy without PCA:")
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    print(f"{name}: {accuracy_score(y_test, y_pred):.4f}")

# Apply PCA (reduce to 5 components)
pca = PCA(n_components=5)
X_pca = pca.fit_transform(X_scaled)
X_train_pca, X_test_pca, y_train_pca, y_test_pca = train_test_split(X_pca, y, test_size=0.2, random_state=42)

# Train and evaluate models (with PCA)
print("\n📉 Accuracy with PCA:")
for name, model in models.items():
    model.fit(X_train_pca, y_train_pca)
    y_pred_pca = model.predict(X_test_pca)
    print(f"{name}: {accuracy_score(y_test_pca, y_pred_pca):.4f}")
```