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

<u>CERTIFICATE</u>

This is to certify that the Lab work entitled “Machine Learning (23CS6PCMAL)” carried out by **Shreyansh Sethiya (1BM22CS269),** 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 a Machine Learning (23CS6PCMAL) work prescribed for the said degree.

Lab Faculty Incharge Name: Sheetal V A Assistant Professor Department of CSE, BMSCE	 **Dr. Kavitha Sooda** Professor & HOD Department of CSE, BMSCE

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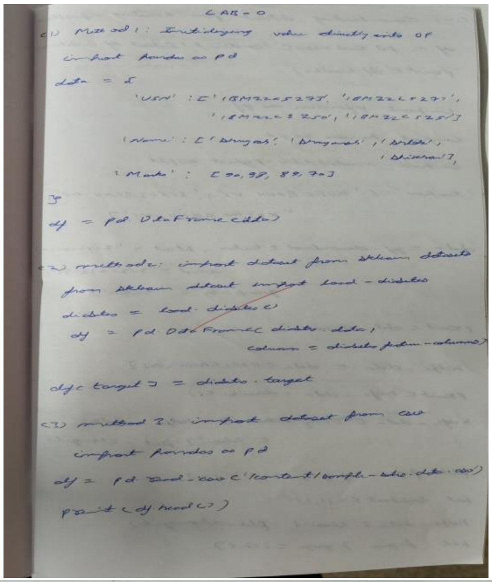
Github Link:

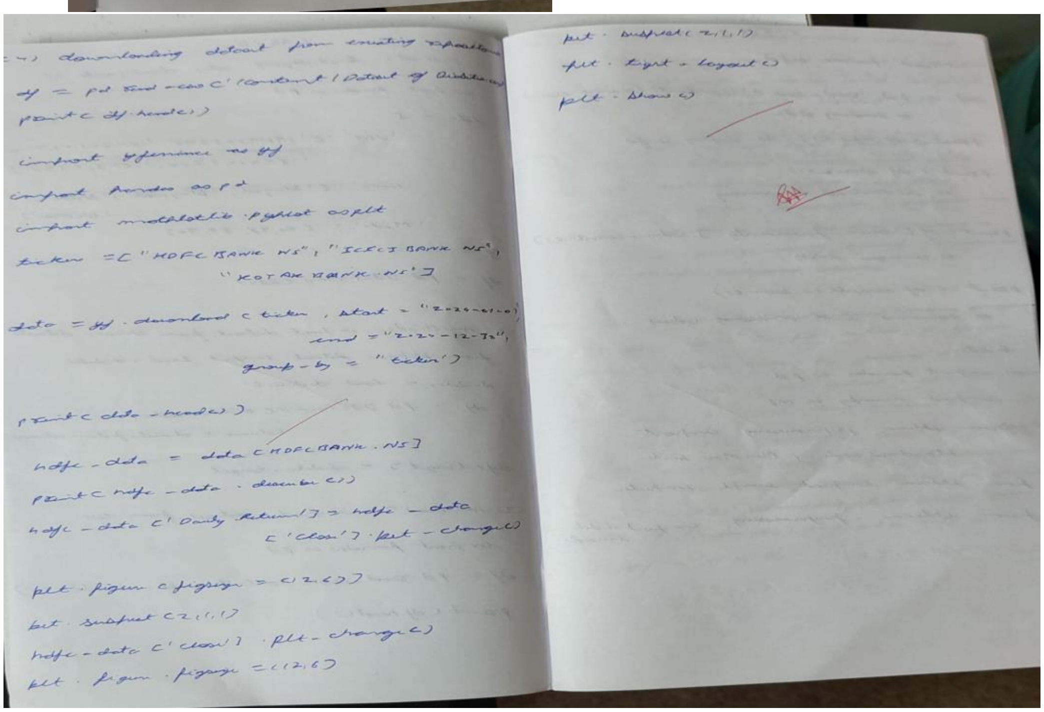
https://github.com/Shreyanshsethiya/6thsem-ML-Lab

Program 1

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

Screenshot





Code:

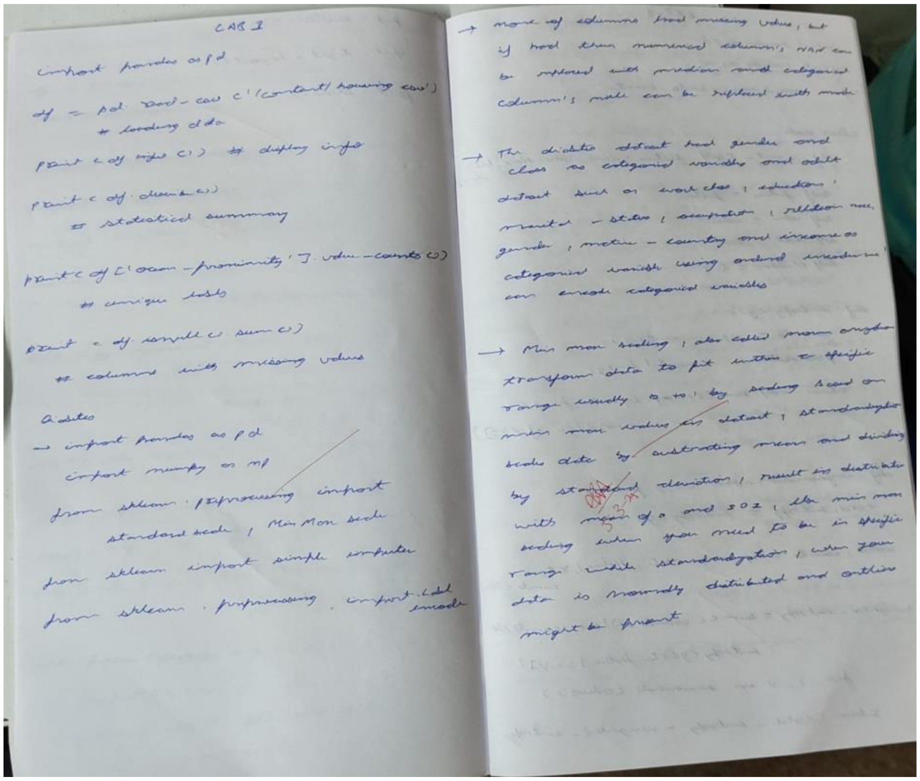
```
import pandas as pd

data={
    'USN':['1BM22CS001','1BM22CS002','1BM22CS003','1BM22CS004','1BM22CS005'],
    'Name':['Ankita','Anita','Amit','Anish','Arun'],
    'Marks':[99,56,96,85,45]
}

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

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

path=r"/content/sample_sales_data.csv"
df=pd.read_csv(path)
print(df)


path=r"/content/Dataset of Diabetes .csv"
df=pd.read_csv(path)
print(df.head())


import yfinance as yf
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=tickers)
print(data)

#HDFCBANK
HDFC=data['HDFCBANK.NS']
HDFC['Daily Return']=HDFC['Close'].pct_change()
print(HDFC)

plt.figure(figsize=(12,6))
plt.subplot(2,1,1)
HDFC['Close'].plot(title='HDFC BANK - Closing Price')
plt.subplot(2,1,2)
HDFC['Daily Return'].plot(title='HDFC BANK - Daily Return',color='orange')
```

```
plt.tight_layout()
plt.show()

#ICICIBANK
ICICI=data['ICICIBANK.NS']
ICICI['Daily Return']=ICICI['Close'].pct_change()
print(ICICI)

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

Program 2

Demonstrate various data pre-processing techniques for a given dataset

Screenshot



LAB 1

import pandas as pd

df = pd.read_csv('/content/housing.csv')
# loading data

print(df.info()) # display info

print(df.describe())
# statistical summary

print(df['ocean_proximity'].value_counts())
# unique labels

print(df.isnull().sum())
# columns with missing values

diabetes
→ import pandas as pd
import numpy as np
from sklearn.preprocessing import
standard scale, Min Max scale
from sklearn import simple imputer
from sklearn.preprocessing import label encode

→ none of columns had missing values, but if had then numerical column's NaN can be replaced with median and categorical column's null can be replaced with mode

→ The diabetes dataset had gender and class as categorical variables and adult dataset such as workclass, education, marital-status, occupation, relation race, gender, native-country and income as categorical variable using ordinal encoder we can encode categorical variables

→ Min max scaling, also called normalization transform data to fit within a specific range usually 0 to 1 by scaling based on min max values in dataset, standardization scale data by subtracting mean and dividing by standard deviation, result in distribution with mean of 0 and SD 1, use min max scaling when you need to be in specific range while standardization, when your data is normally distributed and outliers might be present

3-3-25

Code:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from scipy import stats
df = pd.read_csv(r"/content/Dataset of Diabetes .csv")
df.head(10)
df.shape
print(df.info())
print(df.describe())
missing_values = df.isnull().sum()

# Display columns with missing values
print(missing_values[missing_values > 0])
```

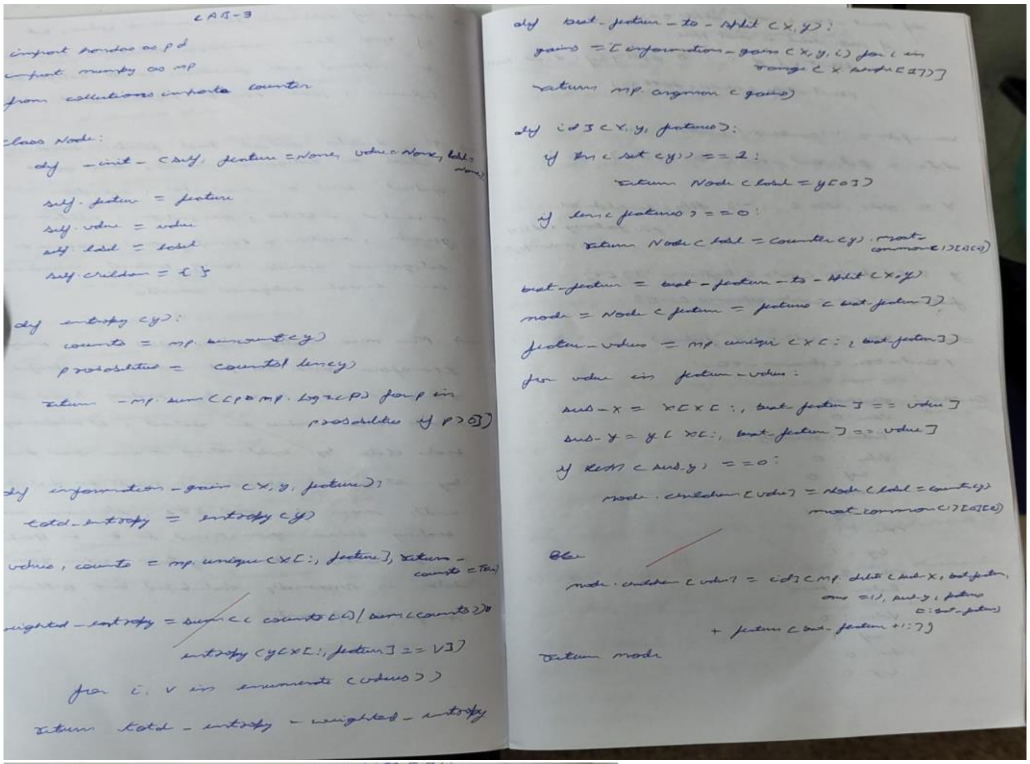
```
#Set the values to some value (zero, the mean, the median, etc.).
# Step 1: Create an instance of SimpleImputer with the median strategy for Age and mean stratergy for Salary
imputer1 = SimpleImputer(strategy="median")
imputer2 = SimpleImputer(strategy="mean")

df_copy=df

# Step 2: Fit the imputer on the "Age" and "Salary"column
# Note: SimpleImputer expects a 2D array, so we reshape the column
imputer1.fit(df_copy[["AGE"]])
imputer2.fit(df_copy[["BMI"]])

# Step 3: Transform (fill) the missing values in the "Age" and "Salary"c column
df_copy["AGE"] = imputer1.transform(df[["AGE"]])
df_copy["BMI"] = imputer2.transform(df[["BMI"]])

# Verify that there are no missing values left
print(df_copy["AGE"].isnull().sum())
print(df_copy["BMI"].isnull().sum())
#Handling Categorical Attributes
#Using Ordinal Encoding for gender COlumn and One-Hot Encoding for City Column

# Initialize OrdinalEncoder
ordinal_encoder = OrdinalEncoder(categories=[["M", "F","f"]])
# Fit and transform the data
df_copy["Gender_Encoded"] = ordinal_encoder.fit_transform(df_copy[["Gender"]])

# Initialize OneHotEncoder
onehot_encoder = OneHotEncoder()

# Fit and transform the "City" column
encoded_data = onehot_encoder.fit_transform(df[["CLASS"]])

# Convert the sparse matrix to a dense array
encoded_array = encoded_data.toarray()

# Convert to DataFrame for better visualization
encoded_df = pd.DataFrame(encoded_array, columns=onehot_encoder.get_feature_names_out(["CLASS"]))
df_encoded = pd.concat([df_copy, encoded_df], axis=1)

df_encoded.drop("Gender", axis=1, inplace=True)
df_encoded.drop("CLASS", axis=1, inplace=True)

print(df_encoded. head())
normalizer = MinMaxScaler()
df_encoded[['BMI']] = normalizer.fit_transform(df_encoded[['BMI']])
df_encoded.head()
scaler = StandardScaler()
```

```
df_encoded[['AGE']] = scaler.fit_transform(df_encoded[['AGE']])
df_encoded.head()
df_encoded_copy1=df_encoded
df_encoded_copy2=df_encoded
df_encoded_copy3=df_encoded

Q1 = df_encoded_copy1['BMI'].quantile(0.25)
Q3 = df_encoded_copy1['BMI'].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
df_encoded_copy1['BMI'] = np.where(df_encoded_copy1['BMI'] > upper_bound, upper_bound,
                    np.where(df_encoded_copy1['BMI'] < lower_bound, lower_bound, df_encoded_copy1['BMI']))

print(df_encoded_copy1.head())
df_encoded_copy2['BMI_zscore'] = stats.zscore(df_encoded_copy2['BMI'])
df_encoded_copy2['BMI'] = np.where(df_encoded_copy2['BMI_zscore'].abs() > 3, np.nan, df_encoded_copy2['BMI'])
# Replace outliers with NaN
print(df_encoded_copy2.head())
df_encoded_copy3['BMI_zscore'] = stats.zscore(df_encoded_copy3['BMI'])
median_salary = df_encoded_copy3['BMI'].median()
df_encoded_copy3['BMI'] = np.where(df_encoded_copy3['BMI_zscore'].abs() > 3, median_salary,
df_encoded_copy3['BMI'])
print(df_encoded_copy3.head())
```

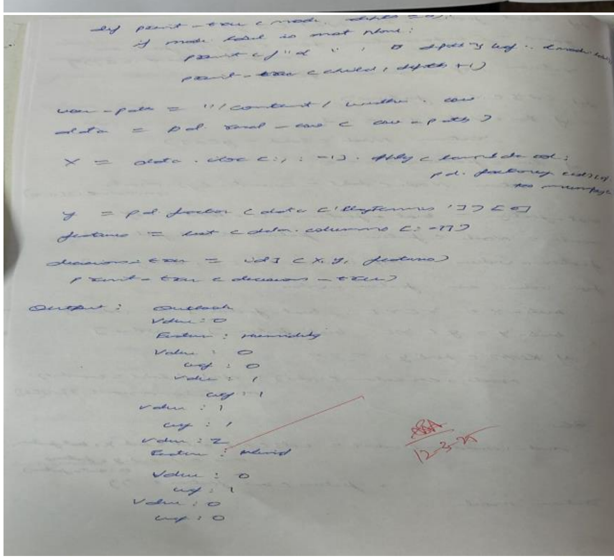
Program 3

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset

Screenshot



```
LAB-3

import pandas as pd
import numpy as np
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
```

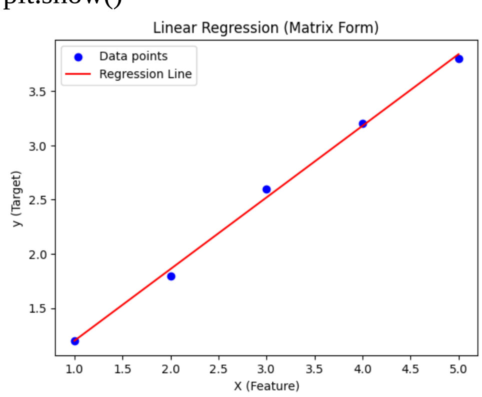


```
def print_tree(node, depth=0):
    if node.label is not None:
        print(f"{' ' * depth}Leaf: {node.label}")
    ...
        print_tree(child, depth+1)

csv_path = '/content/weather.csv'
data = pd.read_csv(csv_path)

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)

Output:  Outlook
         Value: 0
         Feature: Humidity
         Value: 0
           Leaf: 0
         Value: 1
           Leaf: 1
       Value: 1
         Leaf: 1
       Value: 2
       Feature: Wind
         Value: 0
           Leaf: 1
       Value: 0
         Leaf: 0
```

12-3-25

Code:

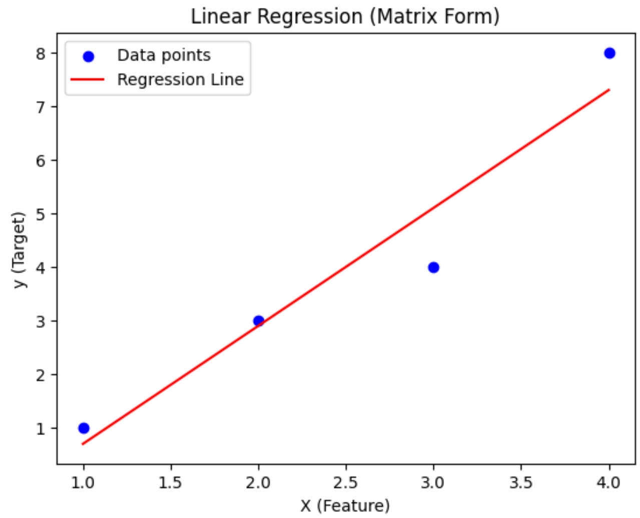
```
import pandas as pd
import matplotlib.pyplot as plt

data={"X":[1,2,3,4,5],
     "Y":[1.2,1.8,2.6,3.2,3.8]}
df=pd.DataFrame(data)
df

Xi=df["X"].mean()
Yi=df["Y"].mean()

df["Xi^2"]=[Xi**2 for Xi in df["X"]]
Xisq=df["Xi^2"].mean()

xiyi=[]
x=df["X"]
y=df["Y"]
for i in range(len(x)):
  xiyi.append(x[i]*y[i])
df["XiYi"]=xiyi
print(df["XiYi"])
XiYi2=df["XiYi"].mean()
print(XiYi2)
a1 = (df["XiYi"].sum() - len(df) * Xi * Yi) / (df["X"].apply(lambda x: x**2).sum() - len(df) * Xi**2)
a0 = Yi - a1 * Xi

x=9
Y=a0+a1*x
print(Y)
plt.scatter(df["X"], df["Y"], color='blue', label='Data points')  # Scatter plot of original data
plt.plot(df["X"], a0 + a1 * df["X"], color='red', label='Regression Line')  # Correct regression line
plt.title('Linear Regression (Matrix Form)')
plt.xlabel('X (Feature)')
plt.ylabel('y (Target)')
plt.legend()
plt.show()
```



```
import numpy as np
import matplotlib.pyplot as plt

X = np.array([1, 2, 3, 4])
y = np.array([1,3,4,8])

X_matrix = np.c_[np.ones(len(X)), X]

theta = np.linalg.inv(X_matrix.T @ X_matrix) @ X_matrix.T @ y

b, m = theta


y_pred = m * X + b


print(f"Slope (m): {m}")
print(f"Intercept (b): {b}")
```

```
Slope (m): 2.2000000000000006
Intercept (b): -1.5
```

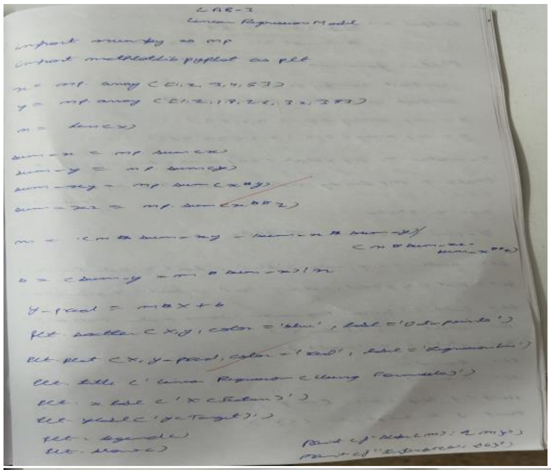
```
plt.scatter(X, y, color='blue', label='Data points')
plt.plot(X, y_pred, color='red', label='Regression Line')
plt.title('Linear Regression (Matrix Form)')
plt.xlabel('X (Feature)')
plt.ylabel('y (Target)')
plt.legend()
plt.show()
```

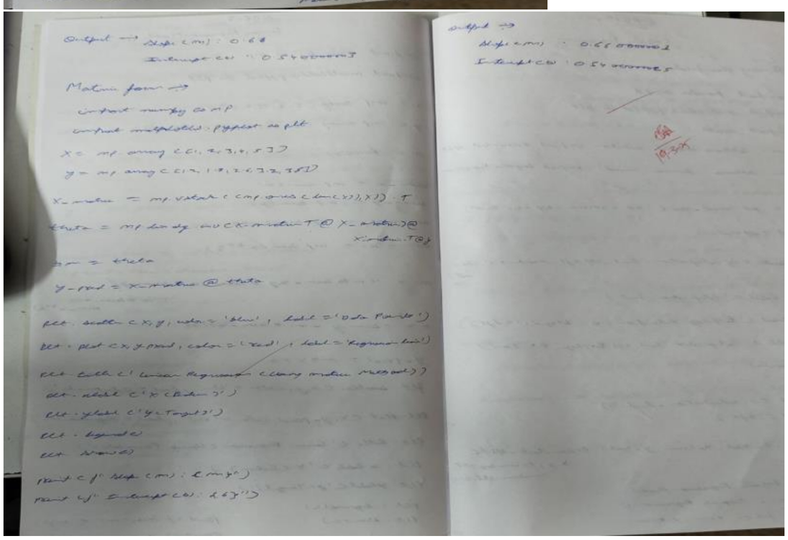


Program 4

Build Logistic Regression Model for a given dataset

Screenshot

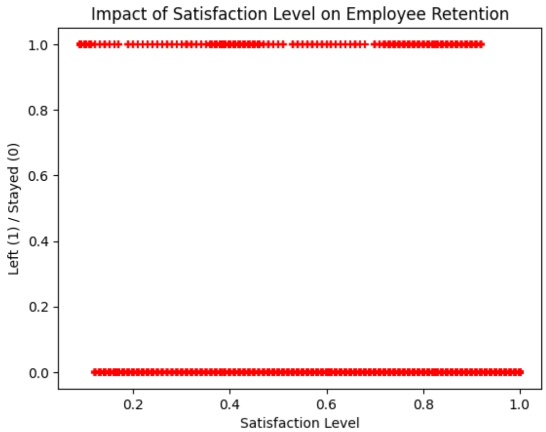




Code:

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

# Load dataset
df = pd.read_csv("/content/HR_comma_sep (2).csv")

# Scatter plot: Employee satisfaction vs Retention
```

```
plt.scatter(df.satisfaction_level, df.left, marker='+', color='red')
plt.xlabel("Satisfaction Level")
plt.ylabel("Left (1) / Stayed (0)")
plt.title("Impact of Satisfaction Level on Employee Retention")
plt.show()

# Define features (X) and target (y)
X = df[['satisfaction_level']]
y = df['left']

# Split dataset (90% train, 10% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.9, random_state=10)

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

# Predictions
y_predicted = model.predict(X_test)

# Model Accuracy
print(f"Model Accuracy: {model.score(X_test, y_test):.4f}")

# Probability predictions
print("Predicted Probabilities:")
print(model.predict_proba(X_test))

# Predict for a specific satisfaction level (e.g., 0.4)
predicted_status = model.predict([[0.4]])
print(f"Prediction for Satisfaction Level 0.4: {'Left' if predicted_status[0] == 1 else 'Stayed'}")

# Logistic function
def sigmoid(x):
    return 1 / (1 + math.exp(-x))

# Custom prediction function
m, b = model.coef_[0][0], model.intercept_[0]
def prediction_function(satisfaction):
    z = m * satisfaction + b
    y = sigmoid(z)
    return y

satisfaction_test = 0.4
print(f"Sigmoid Prediction for Satisfaction Level {satisfaction_test}:
{prediction_function(satisfaction_test):.4f}")
```

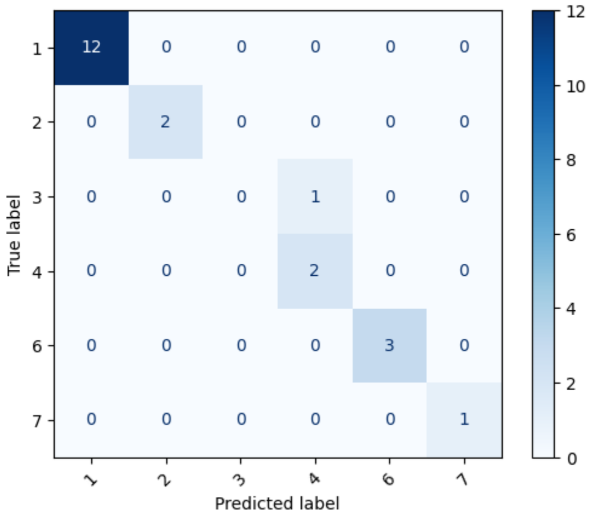



```
Model Accuracy: 0.7707
Predicted Probabilities:
[[0.81879598 0.18120402]
 [0.64435551 0.35564449]
 [0.67008191 0.32991809]
 ...
 [0.85026544 0.14973456]
 [0.93858587 0.06141413]
 [0.90306111 0.09693889]]
Prediction for Satisfaction Level 0.4: Stayed
Sigmoid Prediction for Satisfaction Level 0.4: 0.3644
```

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt

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

# Drop the 'animal_name' column as it is not a relevant feature
X = zoo_data.drop(['animal_name', 'class_type'], axis=1)  # Features
y = zoo_data['class_type']  # Target variable

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

# Initialize the Logistic Regression model for multi-class classification
model = LogisticRegression(multi_class='multinomial', solver='lbfgs', max_iter=200)
# Train the model
model.fit(X_train, y_train)

# Make predictions
```

```
y_pred = model.predict(X_test)
# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy of the Multinomial Logistic Regression model: {accuracy:.2f}")

# Compute confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Adjust display labels to match actual present labels in the test set
unique_classes_in_test = sorted(y_test.unique())

# Display confusion matrix
cm_display = ConfusionMatrixDisplay(confusion_matrix=conf_matrix, display_labels=unique_classes_in_test)
cm_display.plot(cmap='Blues', xticks_rotation=45)
plt.show()
```

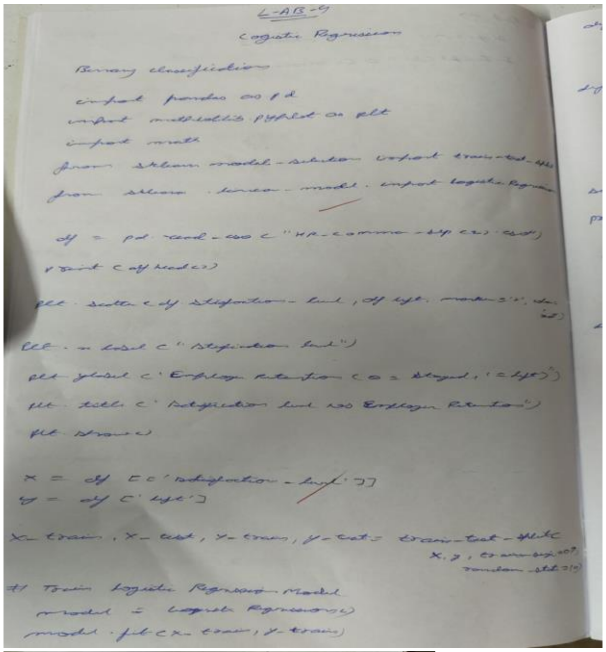
Accuracy of the Multinomial Logistic Regression model: 0.95

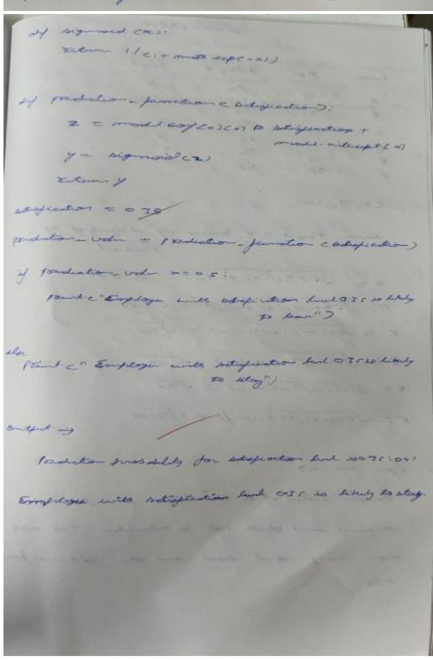


Program 5

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

Screenshot





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  # Attribute to split on
        self.value = value      # Value of the attribute
        self.label = label      # Label if it’s a leaf node
        self.children = {}      # Dictionary of child nodes

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
         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)
# Example dataset
data = pd.DataFrame({
```

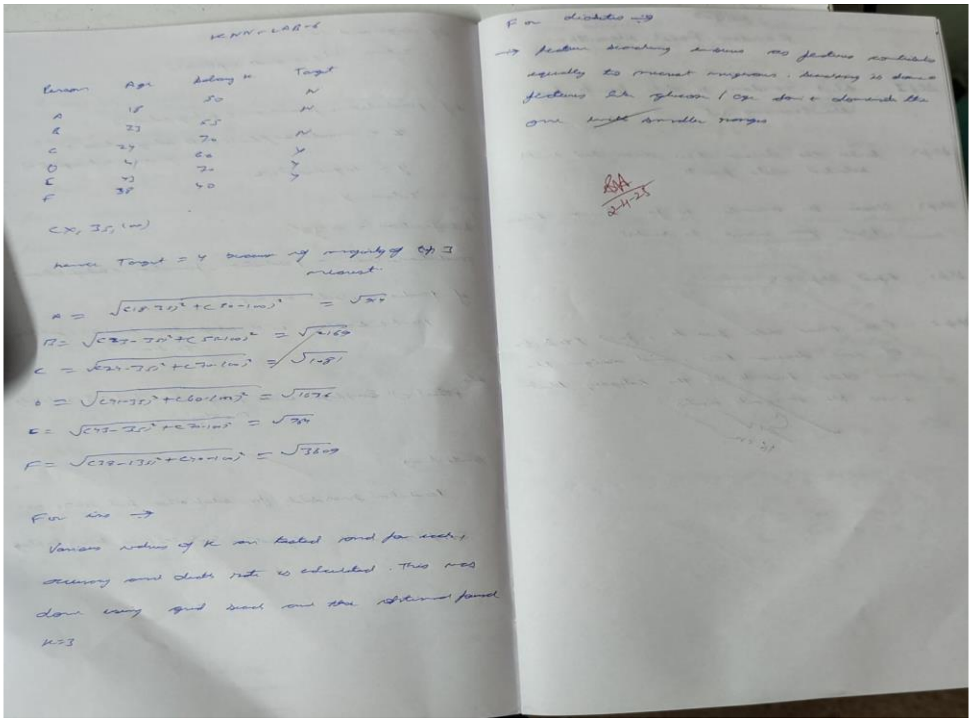
```
    'Outlook': ['Sunny', 'Sunny', 'Overcast', 'Rain', 'Rain', 'Rain', 'Overcast', 'Sunny', 'Sunny', 'Rain', 'Sunny',
'Overcast', 'Overcast', 'Rain'],
    'Temperature': ['Hot', 'Hot', 'Hot', 'Mild', 'Cool', 'Cool', 'Cool', 'Mild', 'Cool', 'Mild', 'Mild', 'Mild', 'Hot', 'Mild'],
    'Humidity': ['High', '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)
```

```
Feature: Outlook
Value: 0
  Feature: Humidity
  Value: 0
    Leaf: 0
  Value: 1
    Leaf: 1
Value: 1
  Leaf: 1
Value: 2
  Feature: Wind
  Value: 0
    Leaf: 1
  Value: 1
    Leaf: 0
```

Program 6

Build KNN Classification model for a given dataset

Screenshot

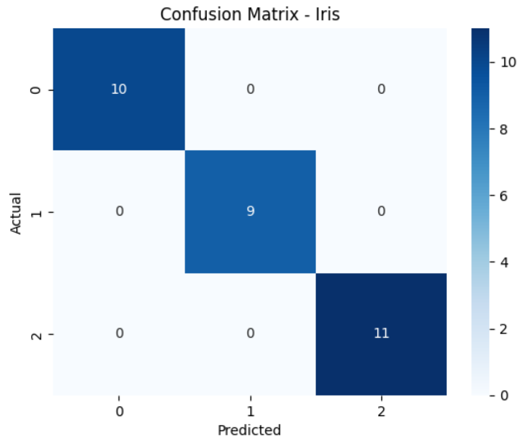


Code:

```
import pandas as pd
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

# Function to train and evaluate KNN model
def knn_classification(data_path, target_column, dataset_name, k=5):
    # Load dataset
    df = pd.read_csv(data_path)

    # Split features and target
    X = df.drop(columns=[target_column])
    y = df[target_column]

    # 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)
```

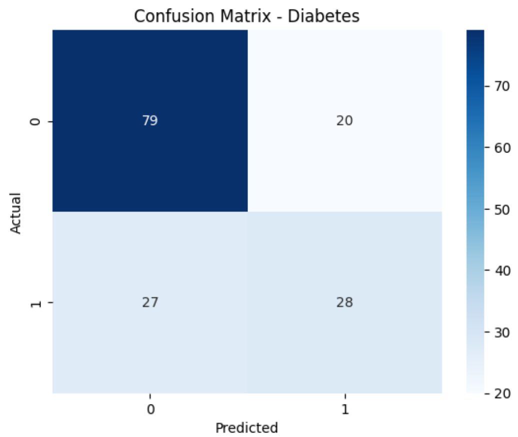
```
    # Feature scaling for better performance
    scaler = StandardScaler()
    X_train = scaler.fit_transform(X_train)
    X_test = scaler.transform(X_test)

    # Train KNN model
    model = KNeighborsClassifier(n_neighbors=k)
    model.fit(X_train, y_train)

    # Make predictions
    y_pred = model.predict(X_test)

    # Evaluate model
    accuracy = accuracy_score(y_test, y_pred)
    print(f'Accuracy of KNN on {dataset_name} dataset: {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 - {dataset_name}')
    plt.show()

# Run KNN classification on both datasets
knn_classification('/content/iris (3).csv', 'species', 'Iris', k=5)
knn_classification('/content/diabetes.csv', 'Outcome', 'Diabetes', k=5)
```

```
Accuracy of KNN on Iris dataset: 1.0000
Classification Report:
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        10
  versicolor       1.00      1.00      1.00         9
   virginica       1.00      1.00      1.00        11

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```



Accuracy of KNN on Diabetes dataset: 0.6948
Classification Report:

	precision	recall	f1-score	support
0	0.75	0.80	0.77	99
1	0.58	0.51	0.54	55
accuracy			0.69	154
macro avg	0.66	0.65	0.66	154
weighted avg	0.69	0.69	0.69	154

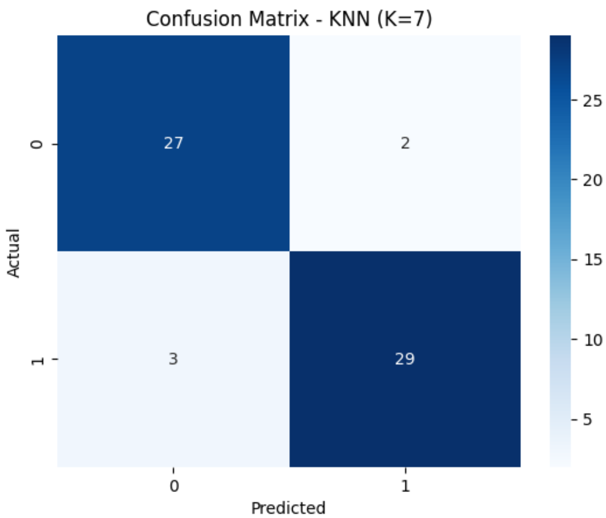


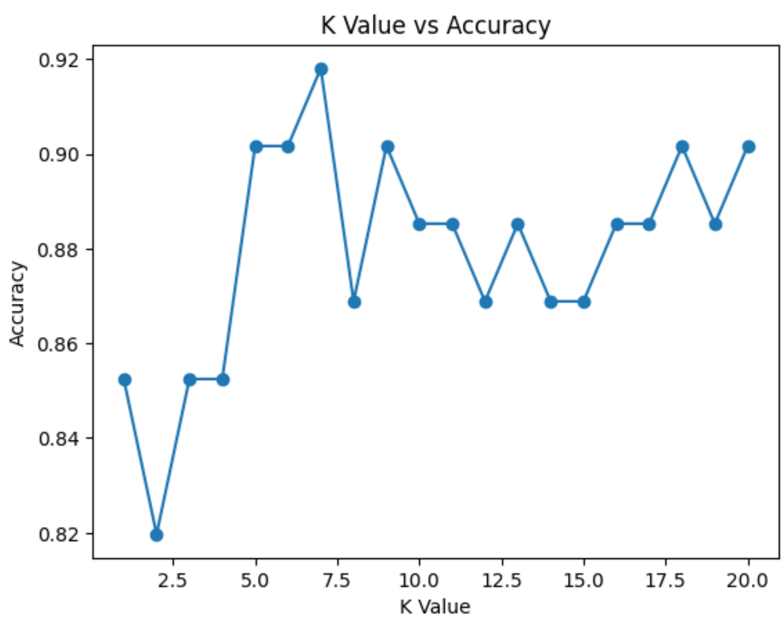

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix,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

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

```python
# 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()
```

```
Best K value: 7
Accuracy with best K (7): 0.9180
Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.93      0.92        29
           1       0.94      0.91      0.92        32

    accuracy                           0.92        61
   macro avg       0.92      0.92      0.92        61
weighted avg       0.92      0.92      0.92        61
```





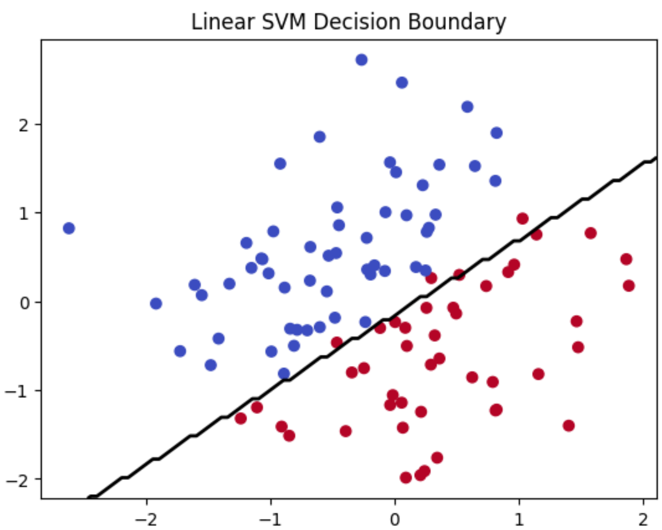
Program 7

Build Support vector machine model for a given dataset

Code:

```
import numpy as np
import matplotlib.pyplot as plt

# Define the Linear SVM class
class LinearSVM:
    def __init__(self, learning_rate=0.001, reg_strength=0.1, num_iterations=1000):
        self.learning_rate = learning_rate
        self.reg_strength = reg_strength
        self.num_iterations = num_iterations

    def fit(self, X, y):
        # Initialize weights and bias
        num_samples, num_features = X.shape
        self.W = np.zeros(num_features)  # Weights
        self.b = 0  # Bias

        # Gradient Descent
        for _ in range(self.num_iterations):
            # Compute the margin (decision function)
            margins = 1 - y * (np.dot(X, self.W) + self.b)
            # Compute gradient
            dw = -2 * np.dot(X.T, (y * (margins > 0))) / num_samples + 2 * self.reg_strength * self.W
            db = -2 * np.sum(y * (margins > 0)) / num_samples

            # Update weights and bias
            self.W -= self.learning_rate * dw
            self.b -= self.learning_rate * db

    def predict(self, X):
        # Make predictions
        return np.sign(np.dot(X, self.W) + self.b)

# Generate toy data (binary classification)
np.random.seed(42)
num_samples = 100
X = np.random.randn(num_samples, 2)
y = np.ones(num_samples)
y[X[:, 0] < X[:, 1]] = -1  # Assign different class based on condition

# Train the Linear SVM
svm = LinearSVM(learning_rate=0.001, reg_strength=0.1, num_iterations=1000)
svm.fit(X, y)

# Predict
```

```python
y_pred = svm.predict(X)

# Visualize the decision boundary
plt.scatter(X[:, 0], X[:, 1], c=y, cmap='coolwarm')
ax = plt.gca()
xlim = ax.get_xlim()
ylim = ax.get_ylim()
xx, yy = np.meshgrid(np.linspace(xlim[0], xlim[1], 100), np.linspace(ylim[0], ylim[1], 100))
Z = svm.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)
plt.contour(xx, yy, Z, levels=[0], linewidths=2, colors='black')
plt.title("Linear SVM Decision Boundary")
plt.show()

# Print accuracy (simple comparison)
accuracy = np.mean(y_pred == y)
print(f"Accuracy: {accuracy * 100:.2f}%")
```

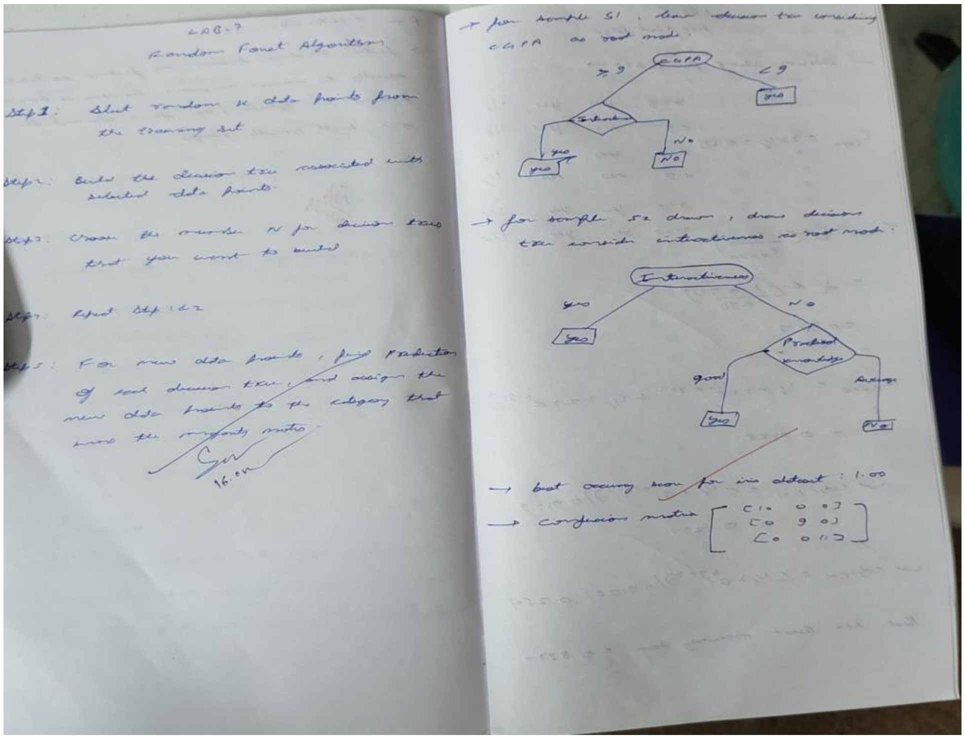


Accuracy: 96.00%

Program 8

Implement Random forest ensemble method on a given dataset

Screenshot

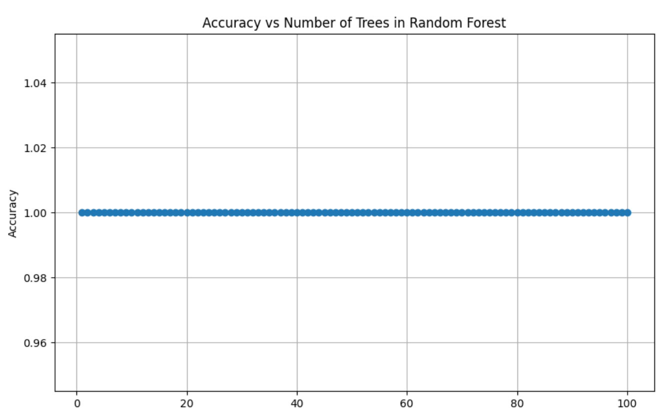


Code:

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt

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

# Assuming last column is the label
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values

# Split into training and test sets (70% train, 30% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
# 1. Train RF Classifier with default n_estimators=10
rf_default = RandomForestClassifier(n_estimators=10, random_state=42)
rf_default.fit(X_train, y_train)
```

```
y_pred_default = rf_default.predict(X_test)
accuracy_default = accuracy_score(y_test, y_pred_default)

print(f"Default RF Accuracy (n_estimators=10): {accuracy_default:.4f}")

best_accuracy = 0
best_n = 0
accuracies = []

for n in range(1, 101):
    rf = RandomForestClassifier(n_estimators=n, random_state=42)
    rf.fit(X_train, y_train)
    y_pred = rf.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    accuracies.append(acc)

    if acc > best_accuracy:
        best_accuracy = acc
        best_n = n

print(f"Best RF Accuracy: {best_accuracy:.4f} with n_estimators = {best_n}")
# Plot accuracy vs. number of trees
plt.figure(figsize=(10, 6))
plt.plot(range(1, 101), accuracies, marker='o')
plt.title("Accuracy vs Number of Trees in Random Forest")
plt.xlabel("Number of Trees (n_estimators)")
plt.ylabel("Accuracy")
plt.grid(True)
plt.show()
```

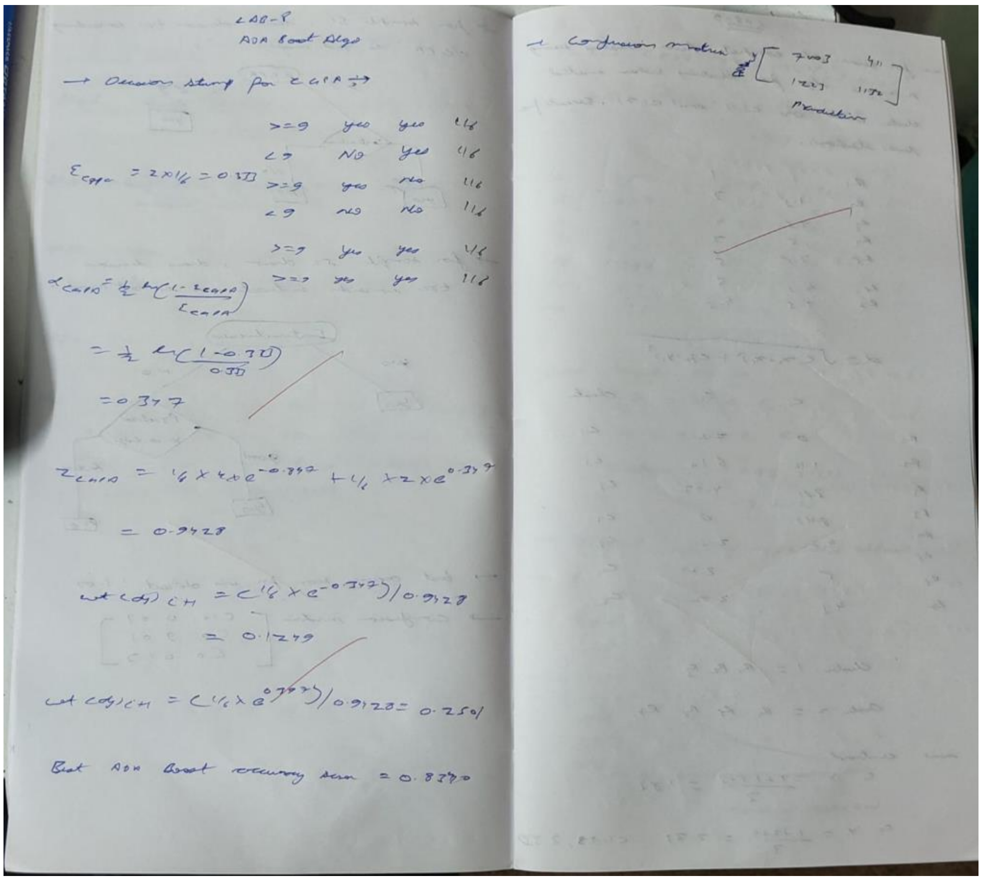
Default RF Accuracy (n_estimators=10): 1.0000
Best RF Accuracy: 1.0000 with n_estimators = 1



Program 9

Implement Boosting ensemble method on a given dataset

Screenshot

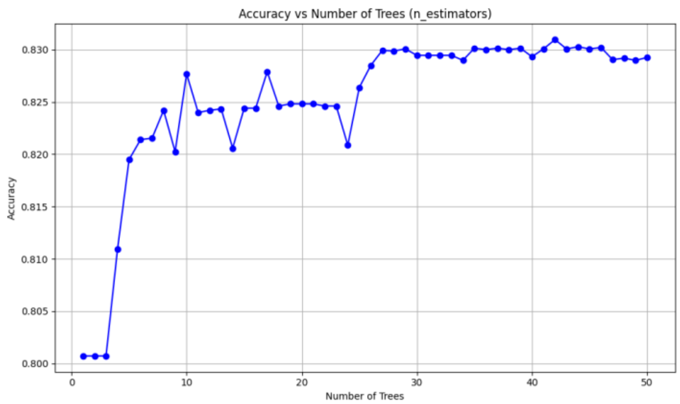


Code:

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

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

# Step 2: Split into features and target
X = df.drop(columns=['income_level'])
y = df['income_level']
```

```python
# Step 3: Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Step 4: AdaBoost with 10 estimators
model_10 = AdaBoostClassifier(n_estimators=10, random_state=42)
model_10.fit(X_train, y_train)
y_pred_10 = model_10.predict(X_test)
accuracy_10 = accuracy_score(y_test, y_pred_10)
conf_matrix_10 = confusion_matrix(y_test, y_pred_10)

print("Accuracy with 10 estimators:", round(accuracy_10, 4))
print("Confusion Matrix (10 estimators):\n", conf_matrix_10)

# Step 5: Fine-tune number of trees (1 to 50)
best_accuracy = 0
best_n = 0
accuracies = []

for n in range(1, 51):
    model = AdaBoostClassifier(n_estimators=n, random_state=42)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    accuracies.append(acc)

    if acc > best_accuracy:
        best_accuracy = acc
        best_n = n

print(f"\nBest Accuracy: {round(best_accuracy, 4)} with n_estimators = {best_n}")

# Step 6: Plot accuracy vs. number of estimators
plt.figure(figsize=(10, 6))
plt.plot(range(1, 51), accuracies, marker='o', linestyle='-', color='blue')
plt.title('Accuracy vs Number of Trees (n_estimators)')
plt.xlabel('Number of Trees')
plt.ylabel('Accuracy')
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
Accuracy with 10 estimators: 0.8277
Confusion Matrix (10 estimators):
 [[10722   387]
 [ 2138  1406]]

Best Accuracy: 0.831 with n_estimators = 42
```

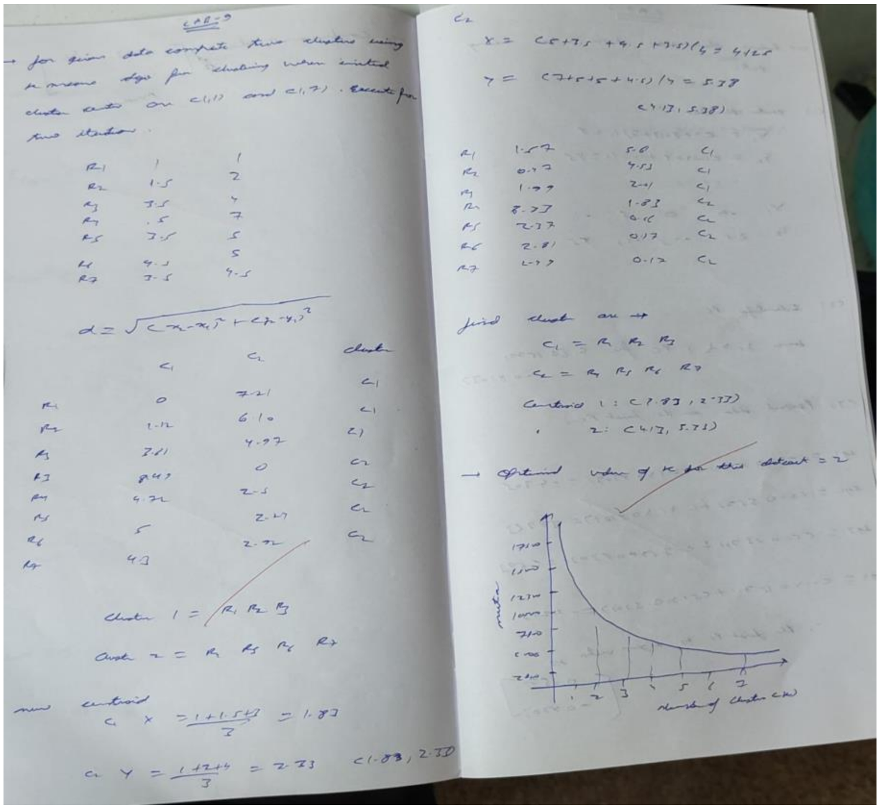


Accuracy vs Number of Trees (n_estimators)
Accuracy
Number of Trees
0.800
0.805
0.810
0.815
0.820
0.825
0.830
0
10
20
30
40
50

Program 10

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

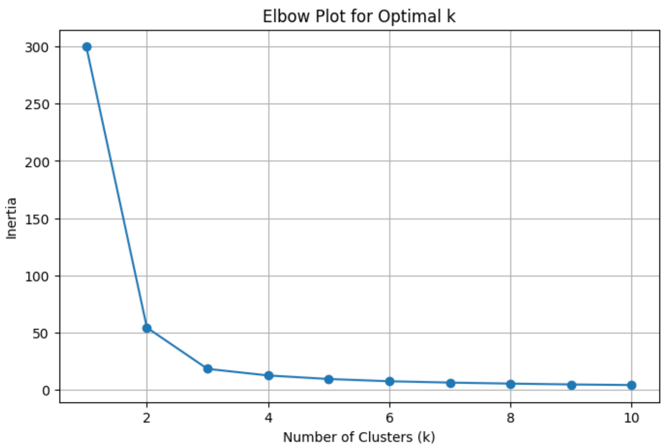
Screenshot



Code:

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

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

# Select only petal length and petal width
X = df[['petal_length', 'petal_width']]

# Optional: Standardize the data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Elbow method to determine optimal k
inertia = []
```

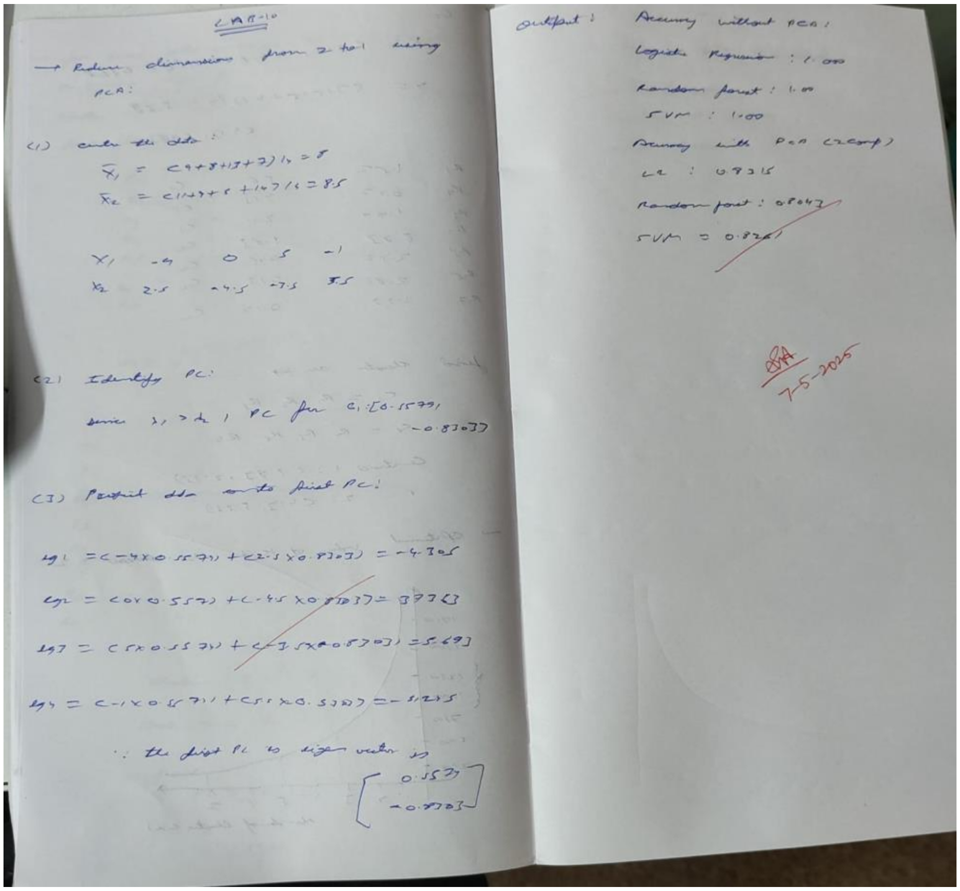
```
k_range = range(1, 11)

for k in k_range:
    model = KMeans(n_clusters=k, random_state=42, n_init=10)
    model.fit(X_scaled)
    inertia.append(model.inertia_)

# Plot the elbow graph
plt.figure(figsize=(8, 5))
plt.plot(k_range, inertia, marker='o')
plt.title('Elbow Plot for Optimal k')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia')
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 (1).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}")
```

🔍 Accuracy without PCA:
SVM: 0.8804
Logistic Regression: 0.8533
Random Forest: 0.8859

📉 Accuracy with PCA:
SVM: 0.8424
Logistic Regression: 0.8641
Random Forest: 0.8533