VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
on

Machine Learning (23CS6PCMAL)

Submitted by

Sarthak Gupta(1BM22CS246)

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 **Sarthak Gupta(1BM22CS246),** 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: **Saritha A.N** Assistant Professor Department of CSE, BMSCE	**Dr. Kavitha Sooda** Professor & HOD Department of CSE, BMSCE

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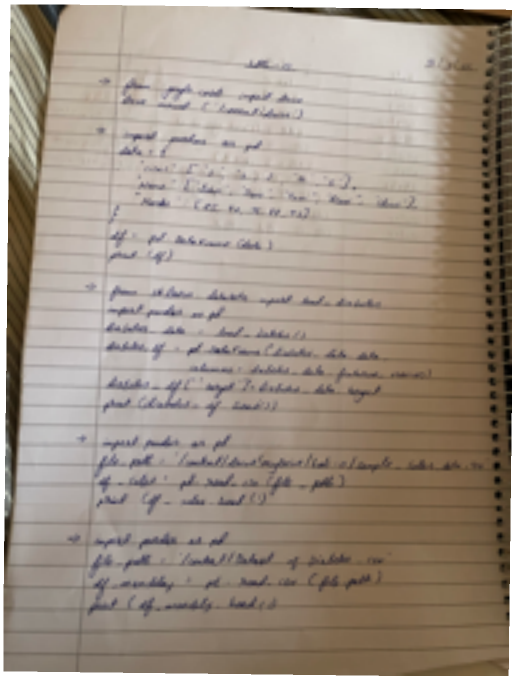
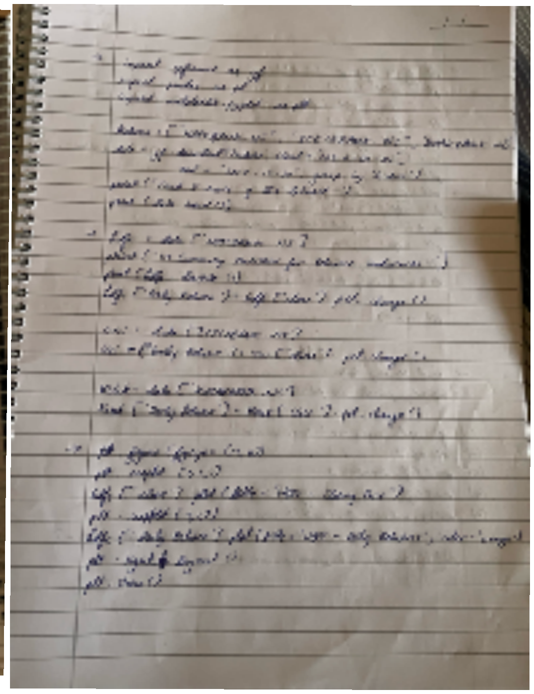
Github Link:

https://github.com/Sarthak5278/ML-Lab

Program 1

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

Screenshot

Code:

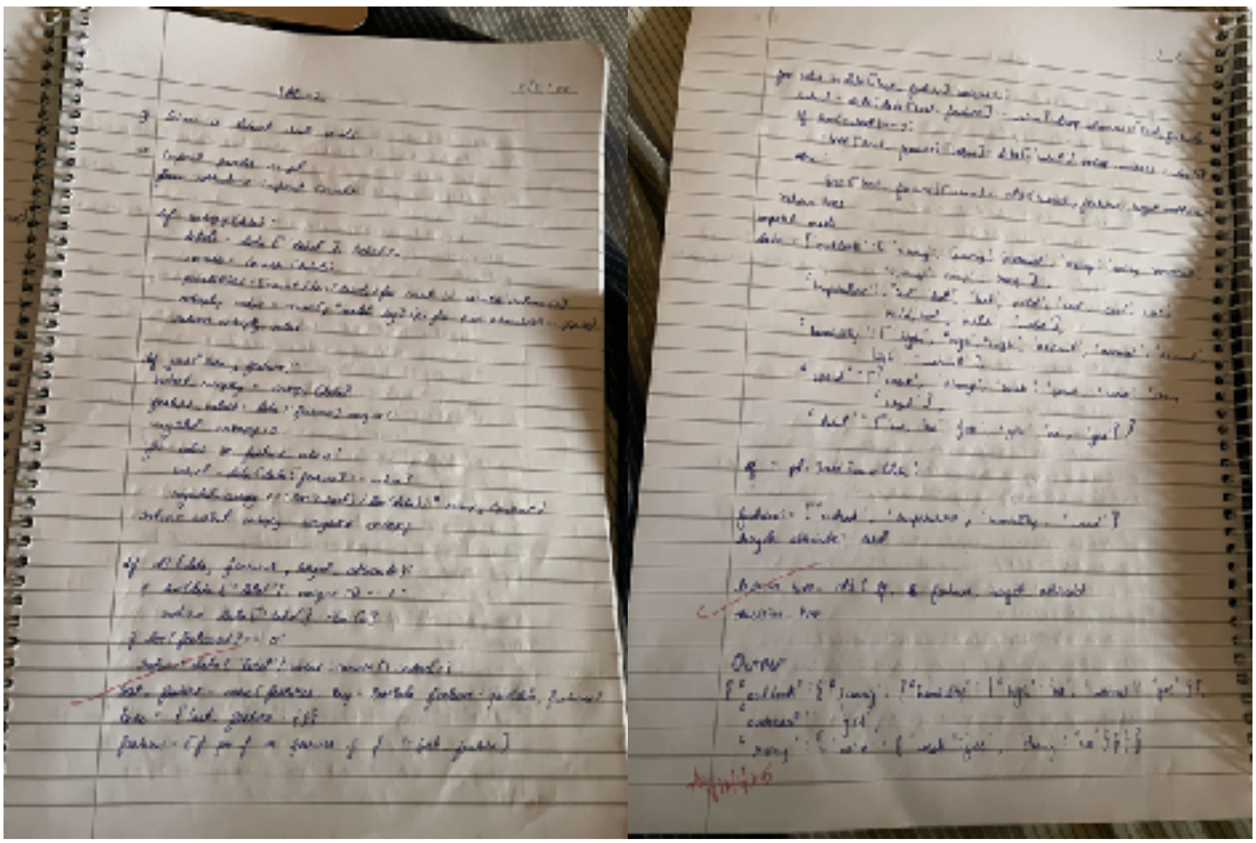
```
import pandas as pd

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()
```

<u>**Program 2**</u>

Demonstrate various data pre-processing techniques for a given dataset

Screenshot



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
```

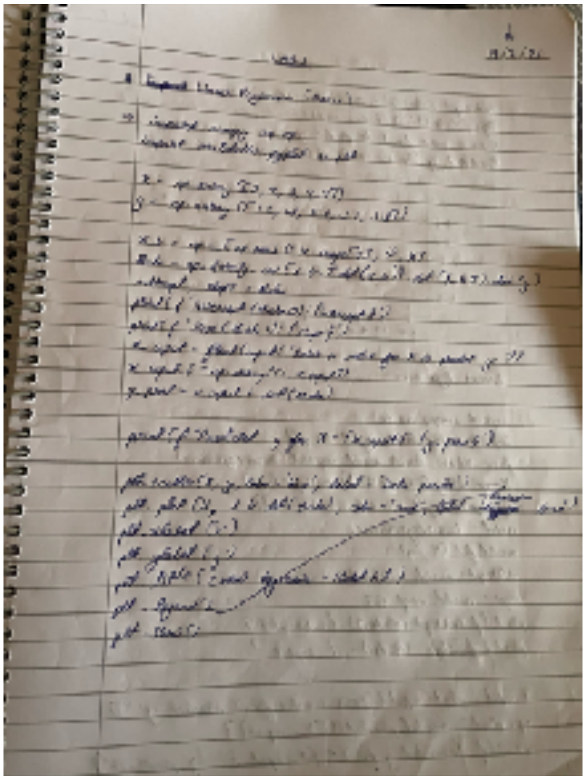
```
print(missing_values[missing_values > 0])

#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']])
```

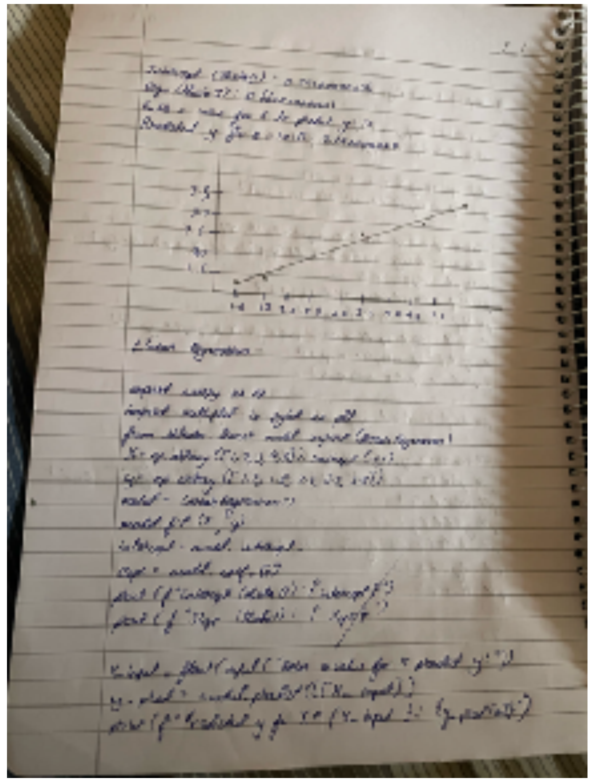
```
df_encoded.head()
df_encoded_copy1=df_encoded
df_encoded_copy2=df_encoded
df_encoded_copy3=df_encoded

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:

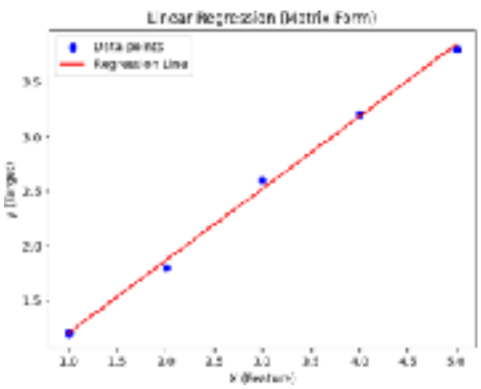




Code:

```
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()
```

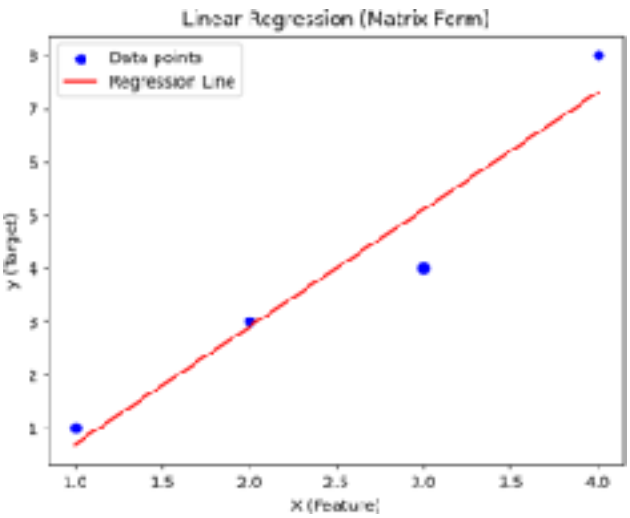


```
import numpy as np
import matplotlib.pyplot as plt

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

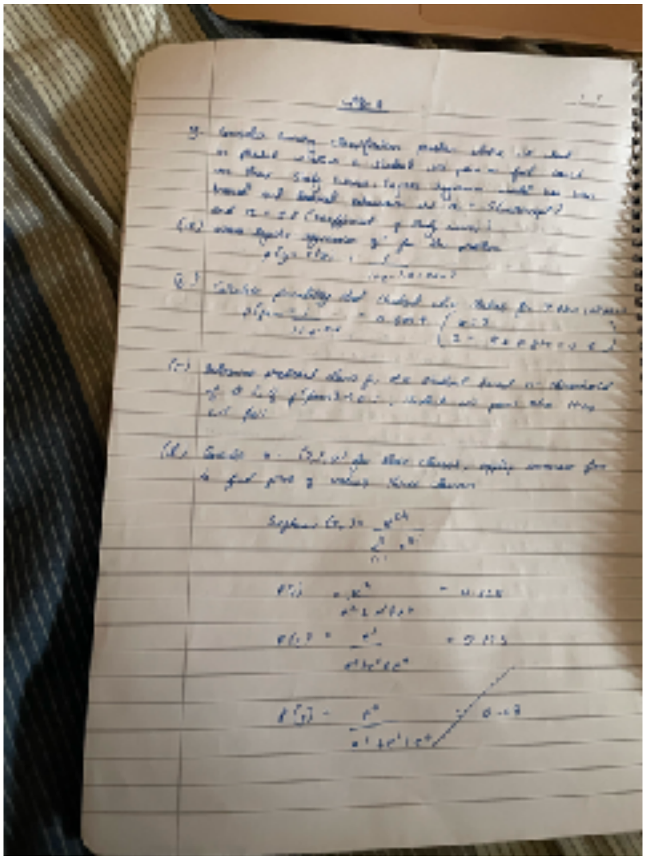
```
plt.scatter(X, y, color='blue', label='Data points')
plt.plot(X, y_pred, color='red', label='Regression Line')
plt.title('Linear Regression (Matrix Form)')
plt.xlabel('X (Feature)')
plt.ylabel('y (Target)')
plt.legend()   plt.show()
```

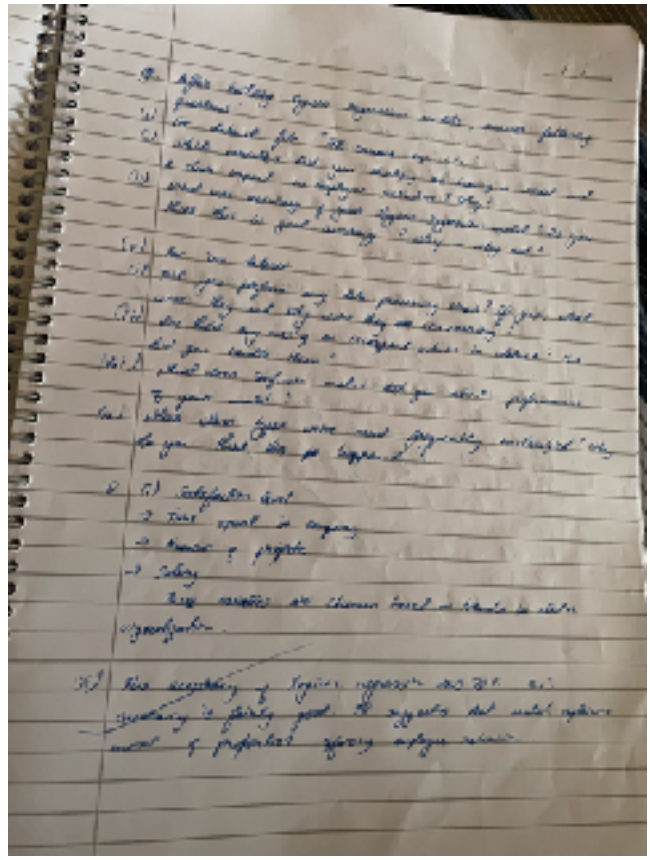


Program 4

Build Logistic Regression Model for a given dataset

Screenshot

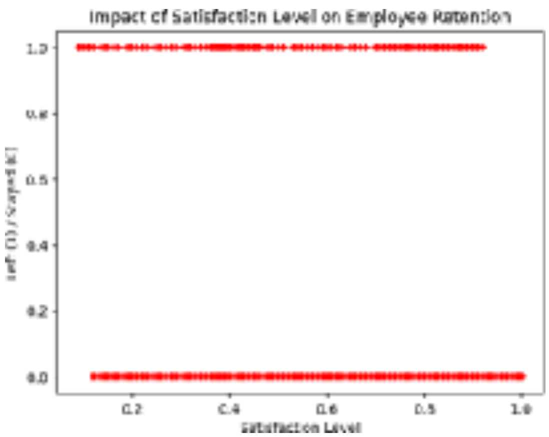




Code:

```
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}")
```

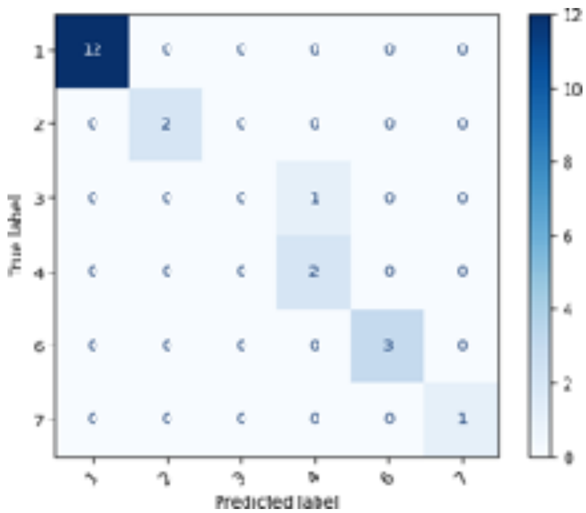



```
Model Accuracy: 0.7707
Predicted Probabilities:
[[0.81879598 0.18120402]
 [0.64435551 0.35564449]
 [0.67008191 0.32991809]
 ...
 [0.85026544 0.14973456]
 [0.93858587 0.06141413]
 [0.90306111 0.09693889]]
Prediction for Satisfaction Level 0.4: Stayed
Sigmoid Prediction for Satisfaction Level 0.4: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

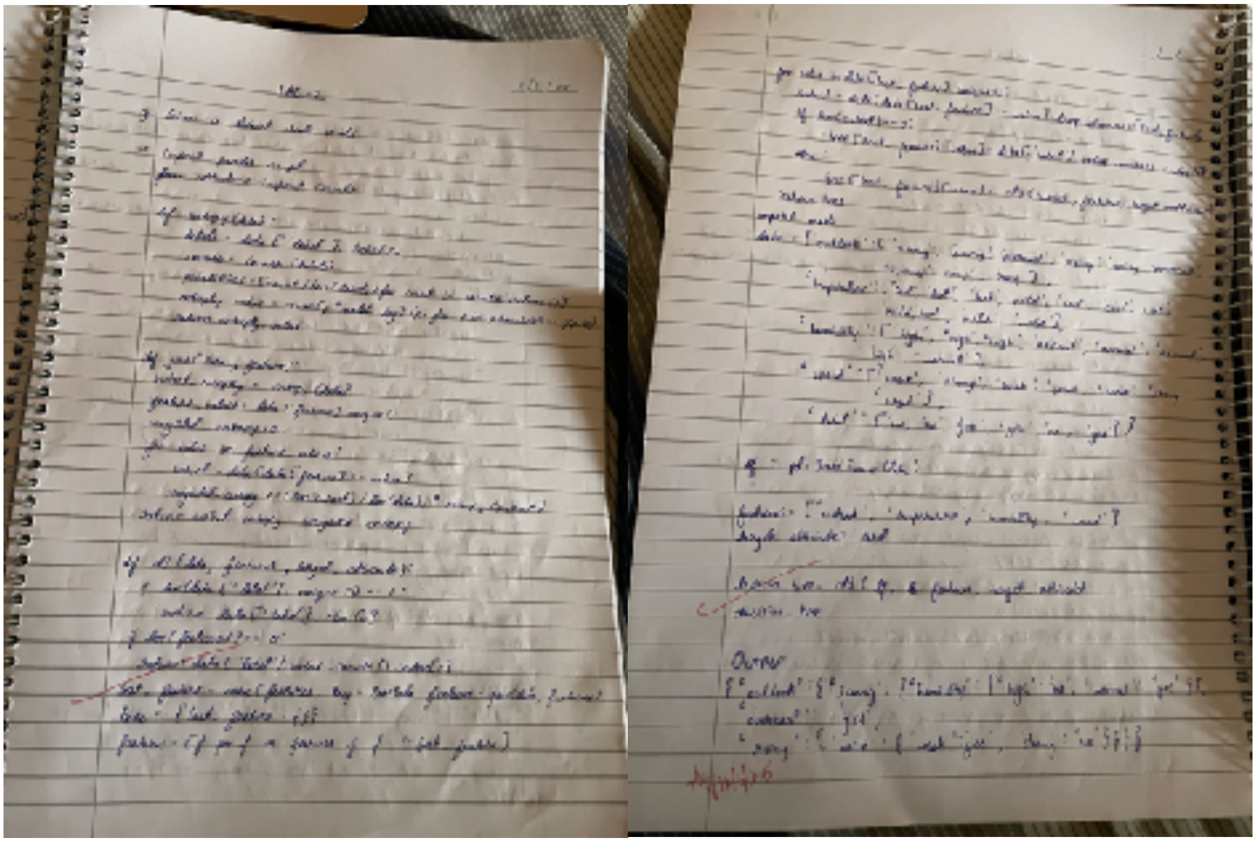
Accuracy of the Multinomial Logistic Regression model: 0.95



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)
```

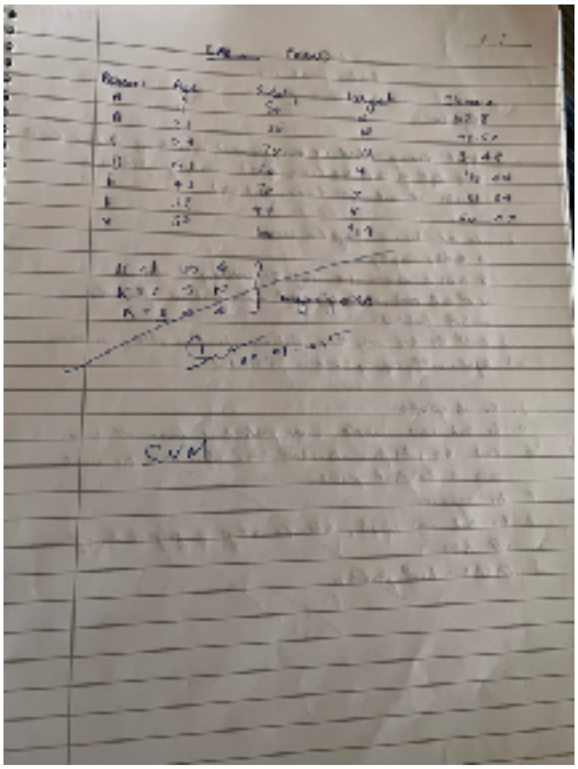
Feature: Outlook
Value: 0

```
  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:

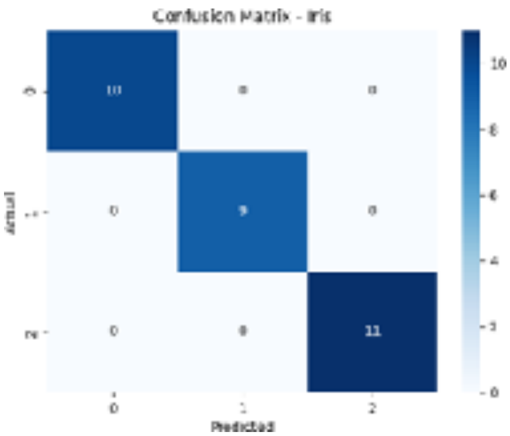
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

# 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:

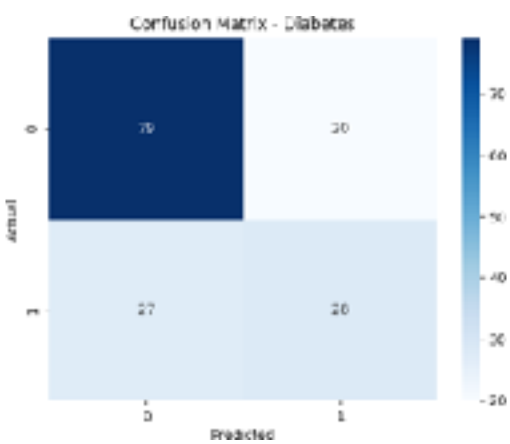
	precision	recall	f1-score	support
setosa	1.00	1.00	1.00	10
versicolor	1.00	1.0 0	1.00	9
virginica	1.00	1.0 0	1.00	11
accuracy			1.0 0	30
macro avg	1.0 0	1.00	1.00	30

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



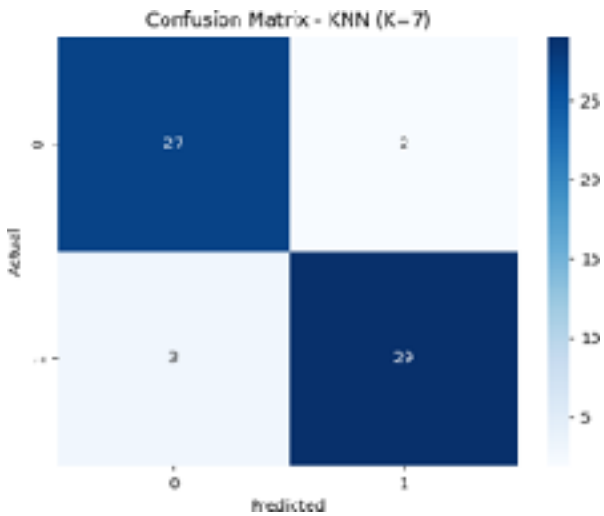

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
```

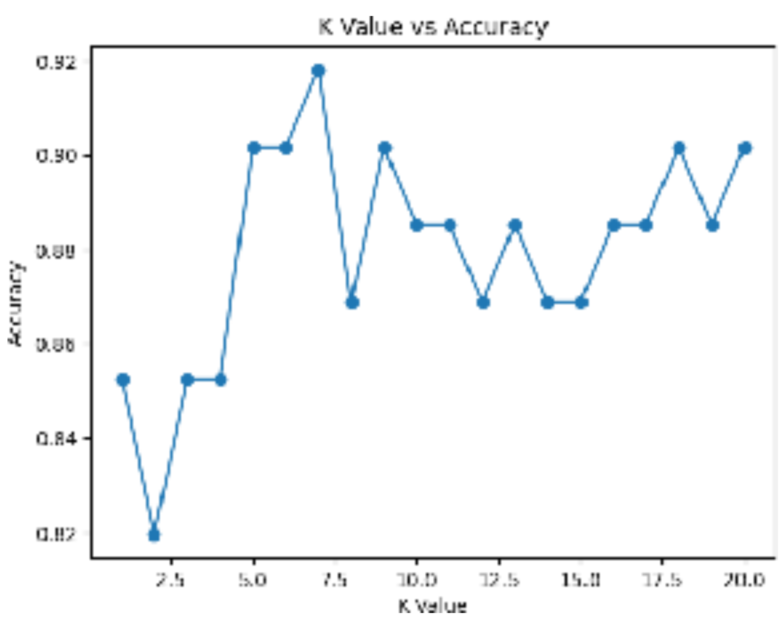
```
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

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





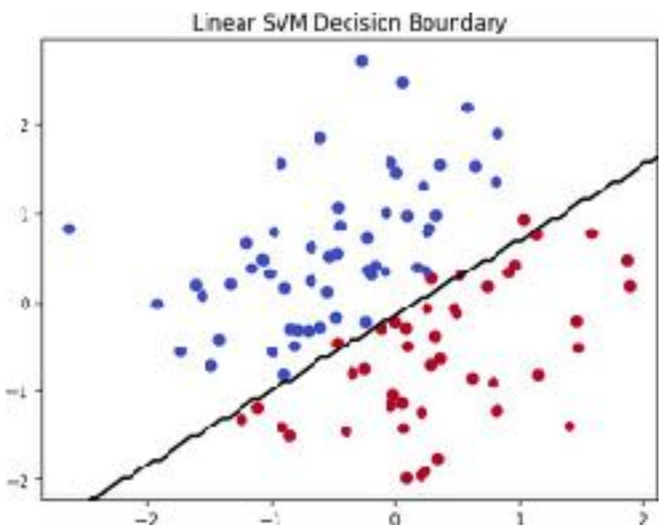
Program 7

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
```

```
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}%")
```

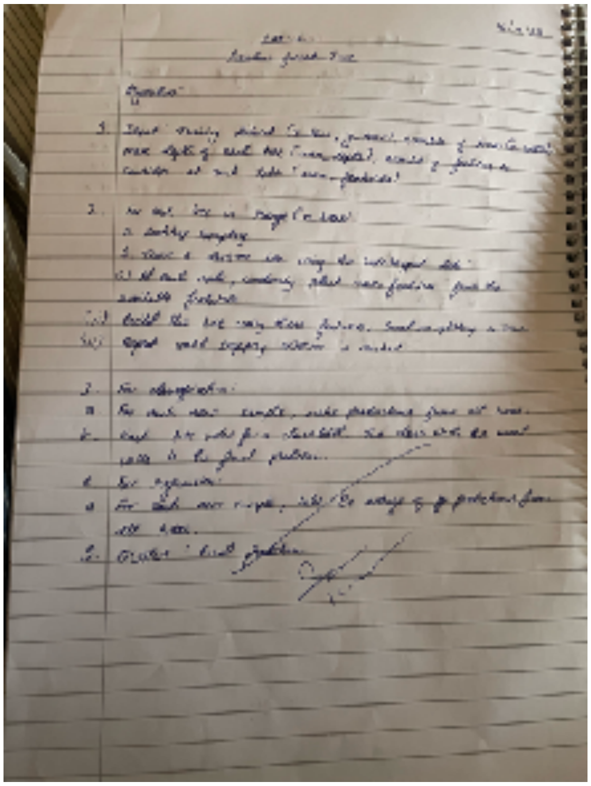


Accuracy: 96.00%

Program 8

Implement Random forest ensemble method on a given dataset

Screenshot

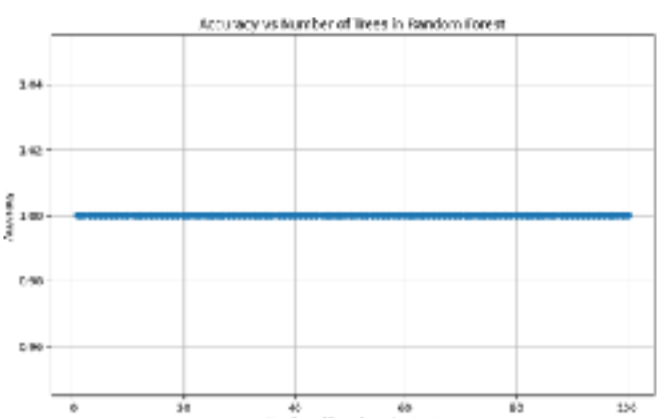


Code:

```
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()
```

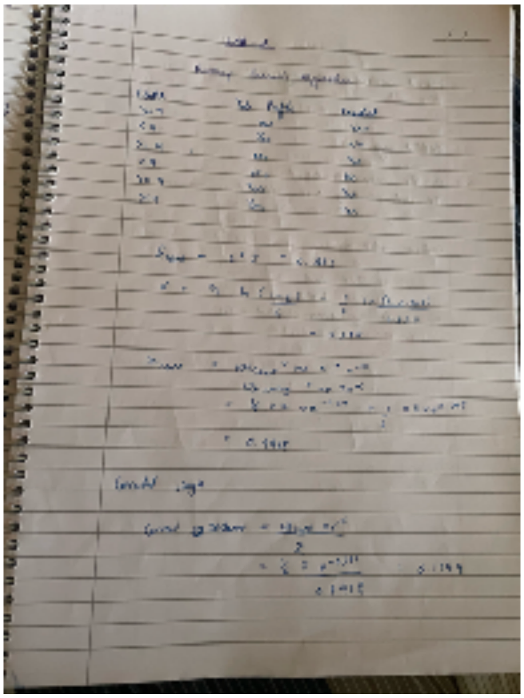
Default RF Accuracy (n_estimators=10): 1.0000
Best RF Accuracy: 1.0000 with n_estimators = 1

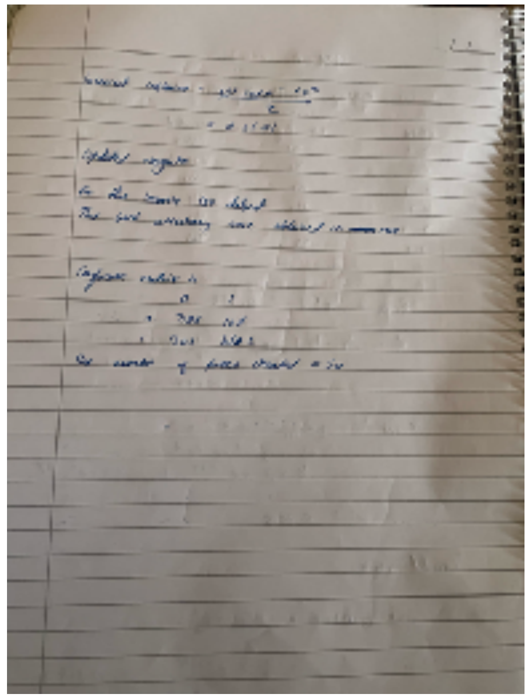


Program 9

Implement Boosting ensemble method on a given dataset

Screenshot



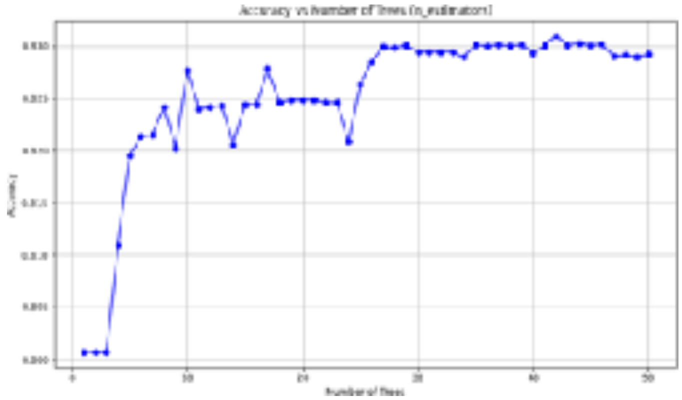


Code:

```
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']

# 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()
```

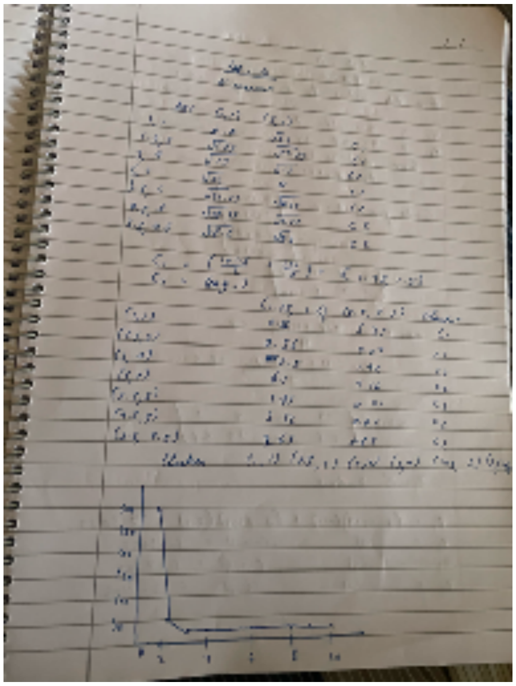
```
Accuracy with 10 estimators: 0.8277
Confusion Matrix (10 estimators):
[[10722   387]
 [ 2138  1406]]

Best Accuracy: 0.831 with n_estimators = 42
```


0
10
40
50

Program 10

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

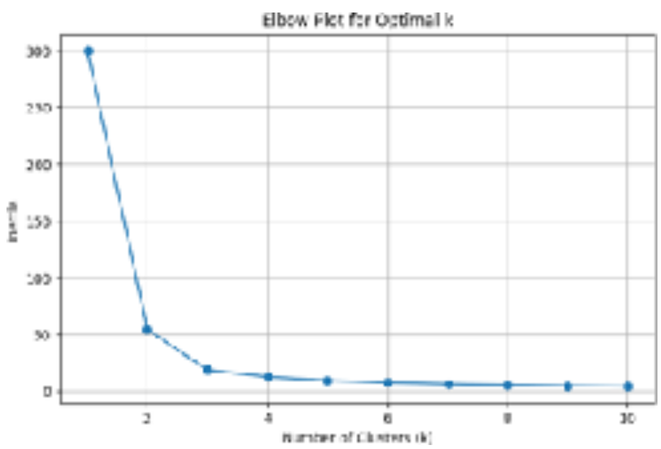
fileScreenshot



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)
```

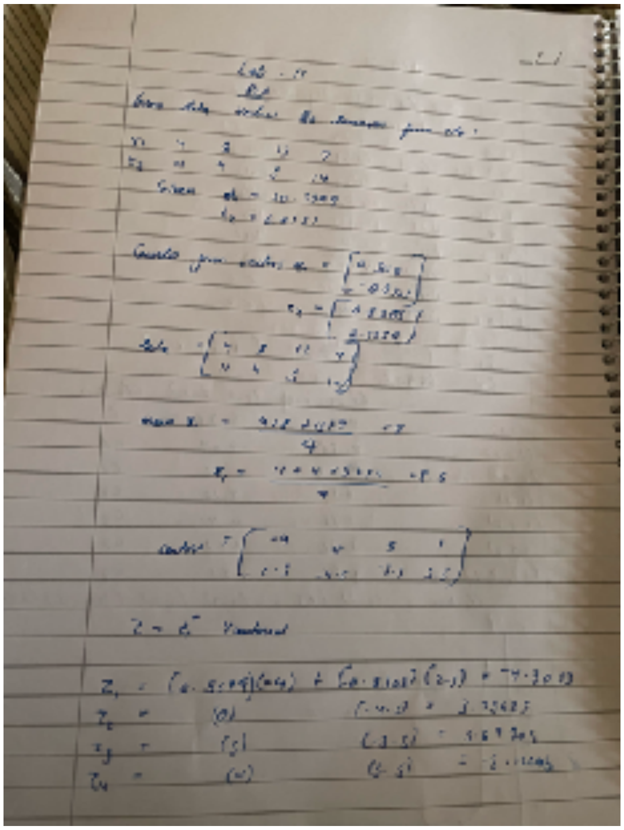
```
for k in k_range:
    model = KMeans(n_clusters=k, random_state=42, n_init=10)
    model.fit(X_scaled)
    inertia.append(model.inertia_)

# 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