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 **Pratham Ganapathy (1BM22CS206),** who is a 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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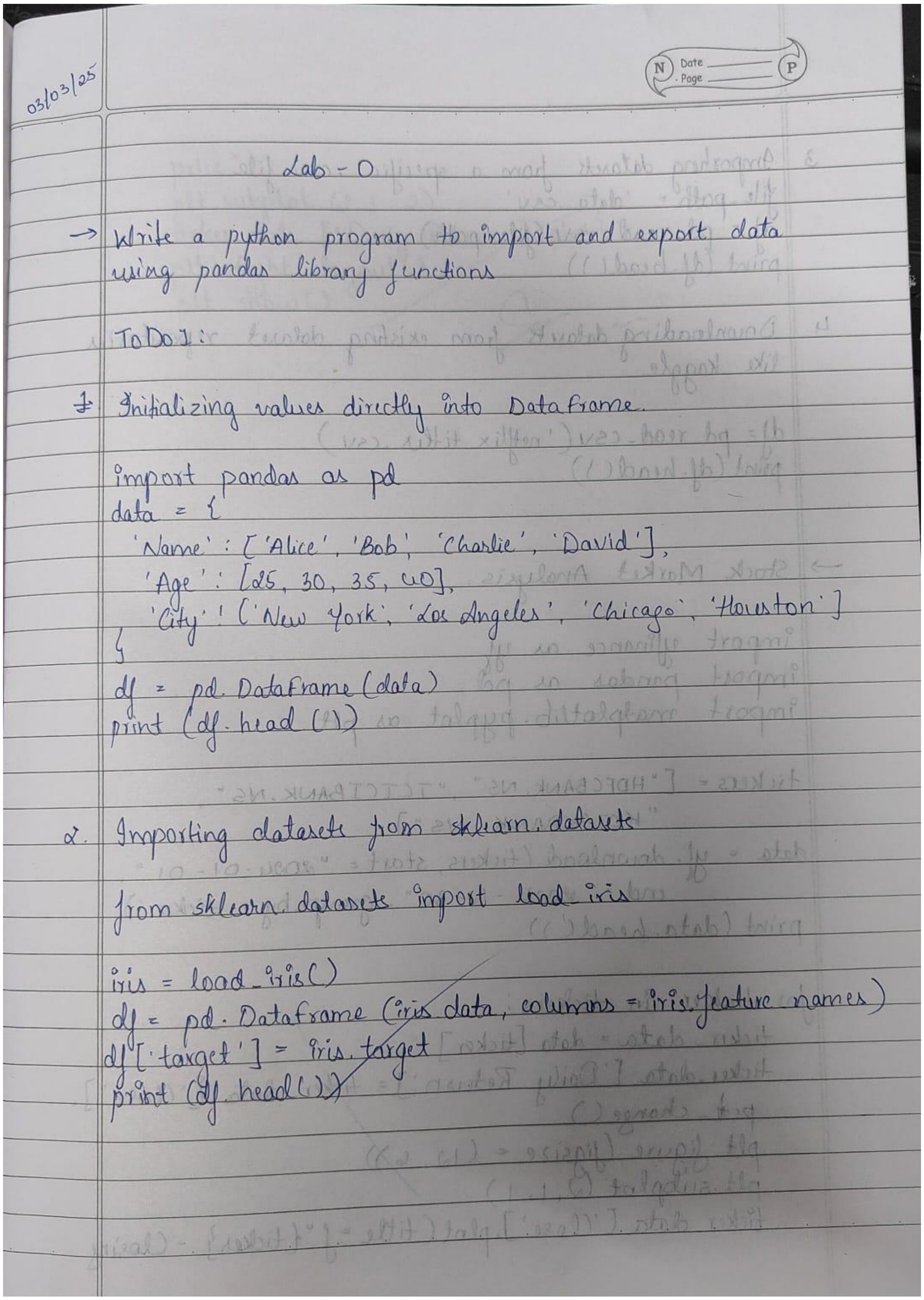
Github Link: https://github.com/PrathamGanapathy/ML-206

Program 1

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

Screenshot:



03/03/25

Lab - 0

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

ToDo 1:

1. Initializing values directly into Dataframe.

```
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 (df.head ())
```

2. Importing datasets from sklearn.datasets

```
from sklearn.datasets import load_iris

iris = load_iris()
df = pd.Dataframe (iris.data, columns = iris.feature_names)
df['target'] = iris.target
print (df.head())
```

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())

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

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

file_path = 'mobiles-dataset-2025.csv'
df = pd.read_csv(file_path, encoding='latin-1') # or 'cp1252' or other suitable encoding
print("Sample data:")
print(df.head())

import pandas as pd
data = {
```

```
    'USN': ['IS001','IS002','IS003','IS004','IS005'],
    'Name': ['Alice', 'Bob', 'Charlie', 'David','Eve'],
    'Marks': [25, 30, 35, 40,45]
}
df = pd.DataFrame(data)
print("Sample data:")
print(df.head())

file_path = '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",encoding='latin-1')
print("Sample data:")
print(df.head())
print("\n")

df =pd.read_csv('sample_sales_data.csv')
print("Sample data:")
print(df.head())
df.to_csv('output.csv',index=False)
print("Data saved to output.csv")

sales_df =pd.read_csv('sample_sales_data.csv')
print("Sample data:")
print(sales_df.head())
sales_by_region =sales_df.groupby('Region')['Sales'].sum()
print("\nTotal sales by region:")
print(sales_by_region)
best_selling_products =sales_df.groupby('Product')['Quantity'].sum().sort_values(ascending=False)
```

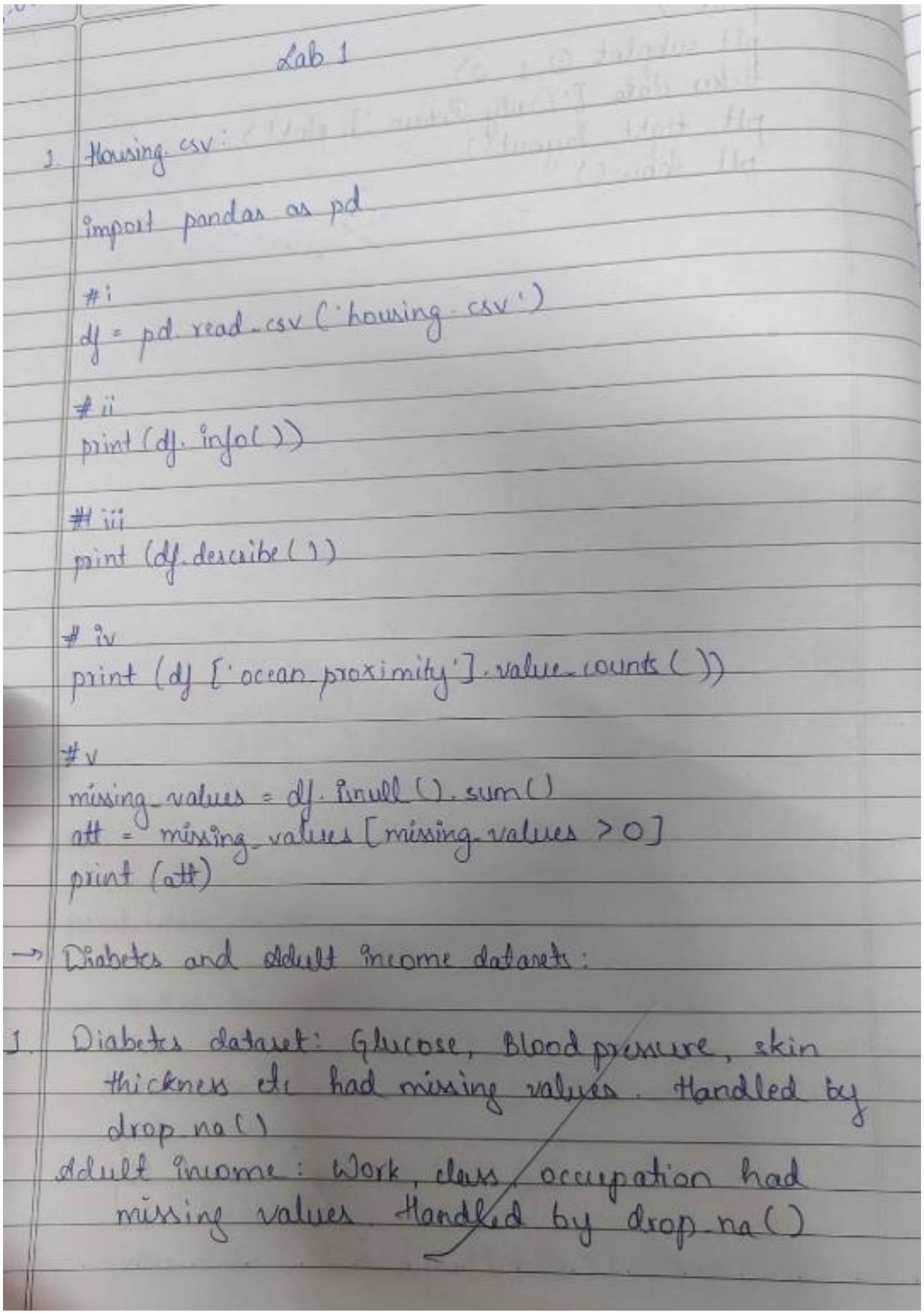
```
print("\nBest-selling products by quantity:")
print(best_selling_products)
sales_by_region.to_csv('sales_by_region.csv')
best_selling_products.to_csv('best_selling_products.csv')
print("Data saved to sales_by_region.csv and best_selling_products.csv")

import yfinance as yf
import matplotlib.pyplot as plt
tickers = ["RELIANCE.NS", "TCS.NS", "INFY.NS"]
data = yf.download(tickers, start="2022-10-01", end="2023-10-01",
                   group_by='ticker')
print("First 5 rows of the dataset:")
print(data.head())
print("\nShape of the dataset:")
print(data.shape)
print("\nColumn names:")
print(data.columns)
print("\n")
reliance_data = data['RELIANCE.NS']
print("\nSummary statistics for Reliance Industries:")
print(reliance_data.describe())
reliance_data['Daily Return'] = reliance_data['Close'].pct_change()
print("\n")
plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
reliance_data['Close'].plot(title="Reliance Industries - Closing Price")
plt.subplot(2, 1, 2)
reliance_data['Daily Return'].plot(title="Reliance Industries - Daily Returns", color='orange')
plt.tight_layout()
plt.show()
reliance_data.to_csv('reliance_stock_data.csv')
```

```
tickers = ["HDFCBANK.NS", "ICICI.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())
print("\nShape of the dataset:")
print(data.shape)
print("\nColumn names:")
print(data.columns)
print("\n")
reliance_data = data['HDFCBANK.NS']
print("\nSummary statistics for Reliance Industries:")
print(reliance_data.describe())
reliance_data['Daily Return'] = reliance_data['Close'].pct_change()
print("\n")
plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
reliance_data['Close'].plot(title="HDFC Industries - Closing Price")
plt.subplot(2, 1, 2)
reliance_data['Daily Return'].plot(title="HDFCIndustries - Daily Returns", color='red')
plt.tight_layout()
plt.show()
reliance_data.to_csv('hdfc_stock_data.csv')
print("\nhdfc stock data saved to 'hdfc_stock_data.csv'.")
```

Program 2

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

Screenshot:



Lab 1

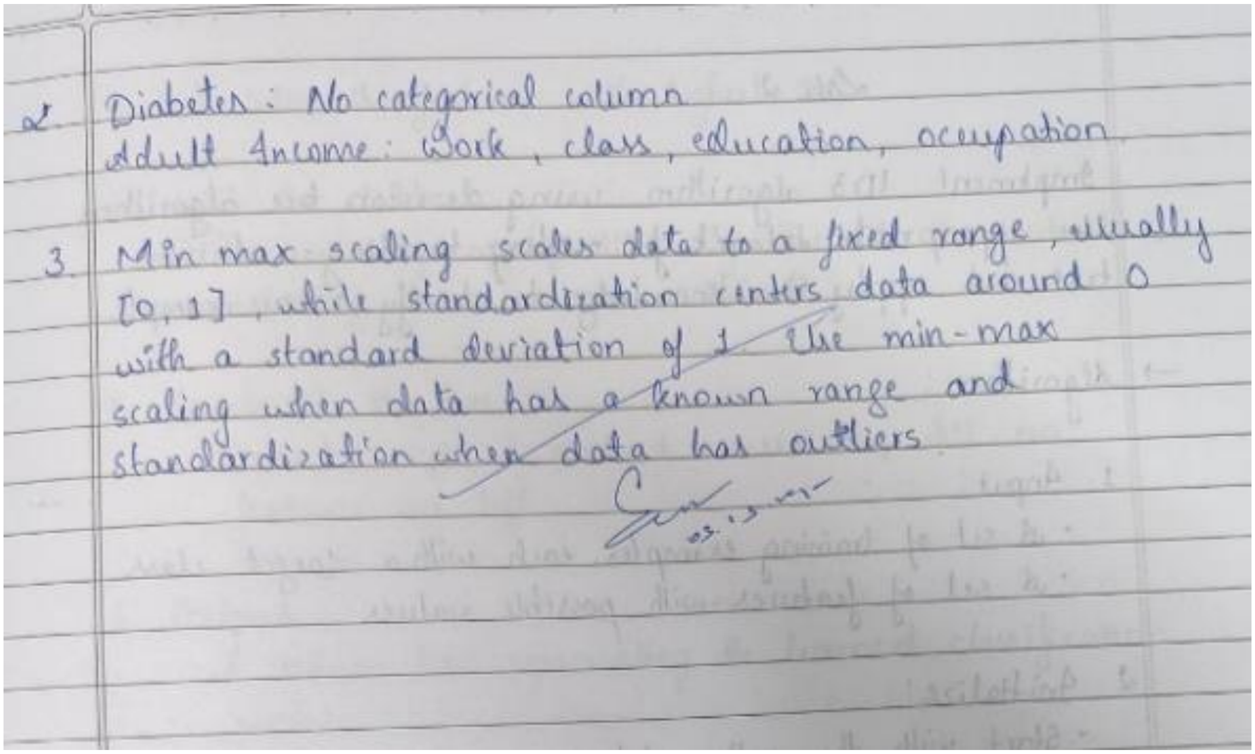
1. Housing.csv:

```
import pandas as pd

#i
df = pd.read_csv('housing.csv')

#ii
print(df.info())

#iii
print(df.describe())

#iv
print(df['ocean_proximity'].value_counts())

#v
missing_values = df.isnull().sum()
att = missing_values[missing_values > 0]
print(att)
```

→ Diabetes and adult income datasets:

1. Diabetes dataset: Glucose, Blood pressure, skin thickness etc had missing values. Handled by drop_na()

Adult income: Work, class, occupation had missing values Handled by drop_na()



2. Diabetes: No categorical column
adult Income: Work, class, education, occupation

3. Min max scaling scales data to a fixed range, usually [0, 1], while standardization centers data around 0 with a standard deviation of 1. Use min-max scaling when data has a known range and standardization when data has outliers

Code:

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.impute import SimpleImputer

try:
    diabetes_df = pd.read_csv('diabetes.csv')
    adult_df = pd.read_csv('adult.csv')
except FileNotFoundError:
    print("Error: Please upload 'diabetes.csv' and 'adult.csv' to your Google Colab environment.")
    exit()

diabetes_df.head(10)
adult_df.head(10)
```

```
diabetes_df.shape
adult_df.shape

#Handling Missing Values
diabetes_numeric_cols = diabetes_df.select_dtypes(include=[np.number]).columns
diabetes_categorical_cols = diabetes_df.select_dtypes(exclude=[np.number]).columns

adult_numeric_cols = adult_df.select_dtypes(include=[np.number]).columns
adult_categorical_cols = adult_df.select_dtypes(exclude=[np.number]).columns

diabetes_numeric_imputer = SimpleImputer(strategy='mean')
adult_numeric_imputer = SimpleImputer(strategy='mean')
diabetes_df[diabetes_numeric_cols] =
diabetes_numeric_imputer.fit_transform(diabetes_df[diabetes_numeric_cols])
adult_df[adult_numeric_cols] = adult_numeric_imputer.fit_transform(adult_df[adult_numeric_cols])

diabetes_categorical_imputer = SimpleImputer(strategy='most_frequent')
adult_categorical_imputer = SimpleImputer(strategy='most_frequent')
diabetes_df[diabetes_categorical_cols] =
diabetes_categorical_imputer.fit_transform(diabetes_df[diabetes_categorical_cols])
adult_df[adult_categorical_cols] =
adult_categorical_imputer.fit_transform(adult_df[adult_categorical_cols])

print("Missing values in Diabetes dataset after imputation:")
print(diabetes_df.isnull().sum())
print("Missing values in Adult Income dataset after imputation:")
print(adult_df.isnull().sum())

adult_df.replace("?", np.nan, inplace=True)
print("Missing values in Adult Income dataset after replacing '?':")
print(adult_df.isnull().sum())
```

```
from sklearn.impute import SimpleImputer

# Identify numeric and categorical columns
adult_numeric_cols = adult_df.select_dtypes(include=[np.number]).columns
adult_categorical_cols = adult_df.select_dtypes(exclude=[np.number]).columns

# Handle missing values in numeric columns using mean imputation
adult_numeric_imputer = SimpleImputer(strategy='mean')
adult_df[adult_numeric_cols] = adult_numeric_imputer.fit_transform(adult_df[adult_numeric_cols])

# Handle missing values in categorical columns using most frequent imputation
adult_categorical_imputer = SimpleImputer(strategy='most_frequent')
adult_df[adult_categorical_cols] =
adult_categorical_imputer.fit_transform(adult_df[adult_categorical_cols])
print("Missing values in Adult Income dataset after imputation:")
print(adult_df.isnull().sum())

from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()

# Encode categorical columns in Diabetes dataset
for col in diabetes_categorical_cols:
    diabetes_df[col] = label_encoder.fit_transform(diabetes_df[col])

# Encode categorical columns in Adult Income dataset
for col in adult_categorical_cols:
    adult_df[col] = label_encoder.fit_transform(adult_df[col])
print("Encoded columns in Diabetes dataset:")
print(diabetes_df.head())
print("Encoded columns in Adult Income dataset:")
print(adult_df.head())
```

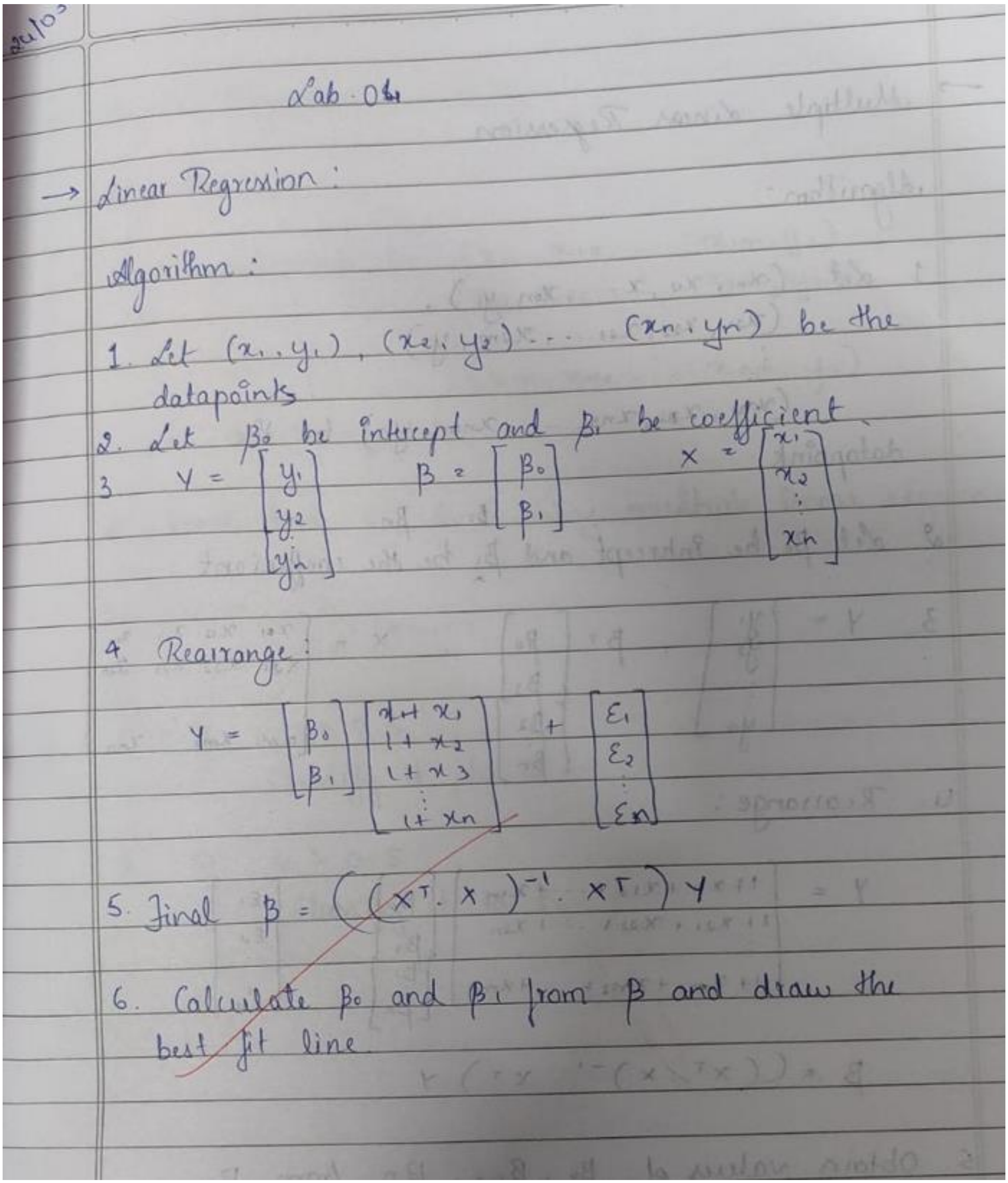
```
#Handling outliers
def remove_outliers(df):
    Q1 = df.quantile(0.25)
    Q3 = df.quantile(0.75)
    IQR = Q3 - Q1
    df_no_outliers = df[~((df < (Q1 - 1.5 * IQR)) | (df > (Q3 + 1.5 * IQR))).any(axis=1)]
    return df_no_outliers

diabetes_df_no_outliers = remove_outliers(diabetes_df)
adult_df_no_outliers = remove_outliers(adult_df)
print("Diabetes dataset shape after removing outliers:", diabetes_df_no_outliers.shape)
print("Adult Income dataset shape after removing outliers:", adult_df_no_outliers.shape)

#Min-max scaling
from sklearn.preprocessing import MinMaxScaler
min_max_scaler = MinMaxScaler()
diabetes_scaled_minmax = pd.DataFrame(min_max_scaler.fit_transform(diabetes_df_no_outliers),
columns=diabetes_df_no_outliers.columns)
adult_scaled_minmax = pd.DataFrame(min_max_scaler.fit_transform(adult_df_no_outliers),
columns=adult_df_no_outliers.columns)
print("Diabetes dataset after Min-Max scaling:")
print(diabetes_scaled_minmax.head())
print("Adult Income dataset after Min-Max scaling:")
print(adult_scaled_minmax.head())

# Initialize Standard Scaler
from sklearn.preprocessing import StandardScaler
standard_scaler = StandardScaler()
diabetes_scaled_standard = pd.DataFrame(standard_scaler.fit_transform(diabetes_df_no_outliers),
columns=diabetes_df_no_outliers.columns)
adult_scaled_standard = pd.DataFrame(standard_scaler.fit_transform(adult_df_no_outliers),
```

```
columns=adult_df_no_outliers.columns)
print("Diabetes dataset after Standard scaling:")
print(diabetes_scaled_standard.head())
print("Adult Income dataset after Standard scaling:")
print(adult_scaled_standard.head())
```

Program 3

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset.

Screenshot:



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Lab 04

→ Linear Regression:

Algorithm:

1. Let $(x_1, y_1), (x_2, y_2) \ldots (x_n, y_n)$ be the datapoints
2. Let β_0 be intercept and β_1 be coefficient.
3. $Y = \begin{bmatrix} y_1 \\ y_2 \\ y_n \end{bmatrix}$ $\beta = \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix}$ $X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$
4. Rearrange:

$$Y = \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} \begin{bmatrix} 1 + x_1 \\ 1 + x_2 \\ 1 + x_3 \\ \vdots \\ 1 + x_n \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}$$

5. Final $\beta = \left((X^T . X)^{-1} . X^T \right) Y$
6. Calculate β_0 and β_1 from β and draw the best fit line.

→ Multiple Linear Regression

Algorithm:

1. Let $(x_{11}, x_{12}, x_{13}, \dots, x_{1m}, y_1)$,
$(x_{21}, x_{22}, x_{23}, \dots, x_{2m}, y_2)$,
$\vdots$
$(x_{n1}, x_{n2}, x_{n3}, \dots, x_{nm}, y_n)$ be the datapoints.

2. Let β_0 be intercept and $\beta_1, \beta_2 \dots \beta_n$ be the coefficient.

3. $Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$, $\beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{bmatrix}$, $X = \begin{bmatrix} x_{11} & x_{12} & x_{13} & \dots & x_{1n} \\ x_{21} & x_{22} & x_{23} & \dots & x_{2n} \\ \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix}$

4. Rearrange:

$$Y = \begin{bmatrix} 1 + x_{11} + x_{12} + \dots + x_{1n} \\ 1 + x_{21} + x_{22} + \dots + x_{2n} \\ \vdots \\ 1 + x_{m1} + x_{m2} + \dots + x_{mn} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_n \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}$$

$$\beta = ((X^T \cdot X)^{-1} \cdot X^T)\, Y$$

5. Obtain values of $\beta_0, \beta_1 \dots \beta_n$ from β

Code:

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

df = pd.read_csv('housing_area_price.csv')
plt.xlabel('area')
plt.ylabel('price')
plt.scatter(df.area,df.price,color='red',marker='+')
new_df = df.drop('price',axis='columns')
new_df
price = df.price
reg = linear_model.LinearRegression()
reg.fit(new_df,price)

#(1) Predict price of a home with area = 3300 sqr ft
reg.predict([[3300]])
reg.coef_
reg.intercept_
3300*135.78767123 + 180616.43835616432

#(2) Predict price of a home with area = 5000 sqr ft
reg.predict([[5000]])

df = pd.read_csv('homeprices_Multiple_LR.csv')
df.bedrooms.median()
df.bedrooms = df.bedrooms.fillna(df.bedrooms.median())
reg = linear_model.LinearRegression()
reg.fit(df.drop('price',axis='columns'),df.price)
reg.coef_
reg.intercept_
```

```
#Find price of home with 3000 sqr ft area, 3 bedrooms, 40 year old
reg.predict([[3000, 3, 40]])
112.06244194*3000 + 23388.88007794*3 + -3231.71790863*40 + 221323.00186540384

df = pd.read_csv('canada_per_capita_income.csv')
print(df.head())
X = df[['year']]
y = df['per capita income (US$)']
reg = LinearRegression()
reg.fit(X, y)
predicted_income_2020 = reg.predict([[2020]])
print(f"Predicted per capita income for Canada in 2020: {predicted_income_2020[0]:.2f}")

plt.scatter(X, y, color='blue')
plt.plot(X, reg.predict(X), color='red')
plt.xlabel('Year')
plt.ylabel('Per Capita Income')
plt.title('Per Capita Income in Canada Over the Years')
plt.show()

df = pd.read_csv('salary.csv')
print(df.head())
print("Missing values in the dataset:")
print(df.isnull().sum())

df['YearsExperience'] = df['YearsExperience'].fillna(df['YearsExperience'].median())
print("\nMissing values after filling:")
print(df.isnull().sum())
X = df[['YearsExperience']]
y = df['Salary']
reg = LinearRegression()
reg.fit(X, y)
```

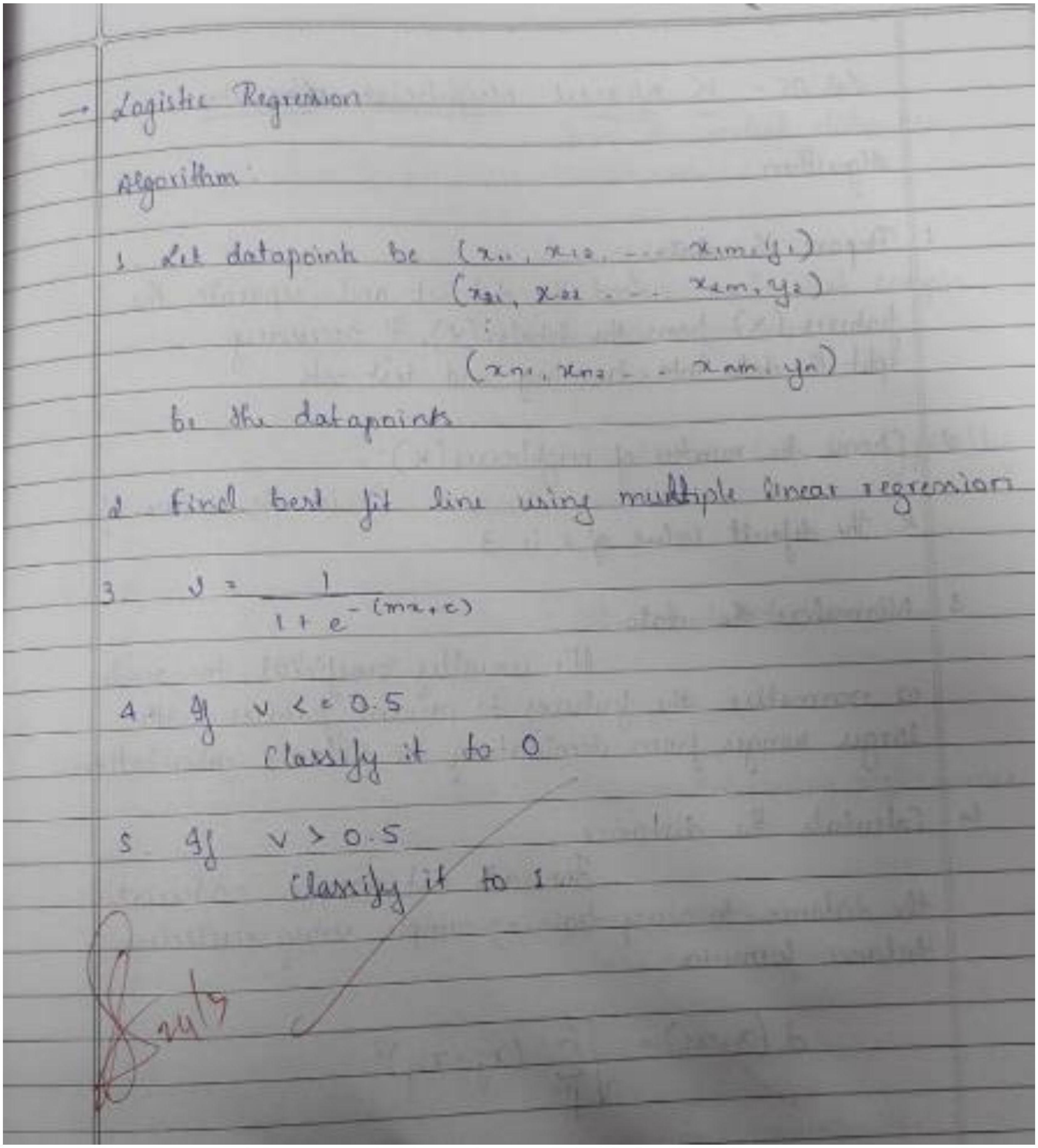
```
predicted_salary_12_years = reg.predict([[12]])
print(f"\nPredicted salary for an employee with 12 years of experience:
${predicted_salary_12_years[0]:,.2f}")

plt.scatter(X, y, color='blue')
plt.plot(X, reg.predict(X), color='red')
plt.xlabel('Years of Experience')
plt.ylabel('Salary')
plt.title('Salary vs. Years of Experience')
plt.show()

def convert_to_numeric(value):
    word_to_num = {
        'zero': 0, 'one': 1, 'two': 2, 'three': 3, 'four': 4, 'five': 5,
        'six': 6, 'seven': 7, 'eight': 8, 'nine': 9, 'ten': 10,
        'eleven': 11, 'twelve': 12, 'thirteen': 13, 'fourteen': 14,
        'fifteen': 15
    }
    return word_to_num.get(value.lower(), value) if isinstance(value, str) else value

df_hiring = pd.read_csv('hiring.csv')
print(df.head())
df_hiring['experience'] = df_hiring['experience'].apply(convert_to_numeric)

df_hiring['experience'].fillna(0, inplace=True)
df_hiring['test_score(out of 10)'].fillna(df_hiring['test_score(out of 10)'].median(), inplace=True)
df_hiring['interview_score(out of 10)'].fillna(df_hiring['interview_score(out of 10)'].median(),
inplace=True)
X_hiring = df_hiring[['experience', 'test_score(out of 10)', 'interview_score(out of 10)']]
y_hiring = df_hiring['salary($)']
reg_hiring = LinearRegression()
reg_hiring.fit(X_hiring, y_hiring)
```

```
candidates = np.array([[2, 9, 6], [12, 10, 10]])
predicted_salaries = reg_hiring.predict(candidates)

for i, candidate in enumerate(candidates):
    print(f"\nPredicted salary for candidate with {candidate[0]} yrs experience, {candidate[1]} test score,
{candidate[2]} interview score: {predicted_salaries[i]:.2f} USD")
plt.scatter(y_hiring, reg_hiring.predict(X_hiring), color='blue', label='Predicted vs Actual')
plt.xlabel("Actual Salary")
plt.ylabel("Predicted Salary")
plt.title("Actual vs Predicted Salary")
plt.legend()
plt.show()
df_companies = pd.read_csv('1000_Companies.csv')
print(df.head())
label_encoder = LabelEncoder()
df_companies['State'] = label_encoder.fit_transform(df_companies['State'])
X_companies = df_companies[['R&D Spend', 'Administration', 'Marketing Spend', 'State']]
y_companies = df_companies['Profit']
df_companies.fillna(df_companies.median(), inplace=True)
reg_companies = LinearRegression()
reg_companies.fit(X_companies, y_companies)
input_data = np.array([[91694.48, 515841.3, 11931.24, label_encoder.transform(['Florida'])[0]]])
predicted_profit = reg_companies.predict(input_data)
print(f"Predicted profit: {predicted_profit[0]:.2f} USD")
plt.scatter(y_companies, reg_companies.predict(X_companies), color='blue', label='Predicted vs
Actual')
plt.xlabel("Actual Profit")
plt.ylabel("Predicted Profit")
plt.title("Actual vs Predicted Profit")
plt.legend()
plt.show()
```

Program 4

Build Logistic Regression Model for a given dataset.

Screenshot:



→ Logistic Regression

Algorithm:

1. Let datapoints be $(x_{11}, x_{12}, \ldots x_{1m}, y_1)$
$(x_{21}, x_{22} \ldots x_{2m}, y_2)$
$\vdots$
$(x_{n1}, x_{n2} \ldots x_{nm}, y_n)$
be the datapoints

2. Find best fit line using multiple linear regression

3. $y = \dfrac{1}{1 + e^{-(mx+c)}}$

4. If $y <= 0.5$
Classify it to 0

5. If $y > 0.5$
Classify it to 1

Code:

```
import pandas as pd
```

```
import seaborn as sns
import matplotlib.pyplot as plt

df = pd.read_csv("HR_comma_sep.csv")
print(df.info())
numericCols = df.select_dtypes(include=['float64', 'int64']).columns
plt.figure(figsize=(10, 8))
sns.heatmap(df[numericCols].corr(), annot=True, cmap='coolwarm', fmt='.2f')
plt.title("Correlation Matrix (Numeric Features)")
plt.show()

plt.figure(figsize=(8, 6))
sns.countplot(x='salary', hue='left', data=df)
plt.title("Impact of Salary on Employee Retention")
plt.xlabel("Salary Level")
plt.ylabel("Employee Count")
plt.show()

import pandas as pd
df = pd.read_csv("zoo-data.csv")
print(df.info())
print(df.head())
print(df.isnull().sum())
df.drop(columns=['animal_name'], inplace=True)
X = df.drop(columns=['class_type'])
y = df['class_type']

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y)
```

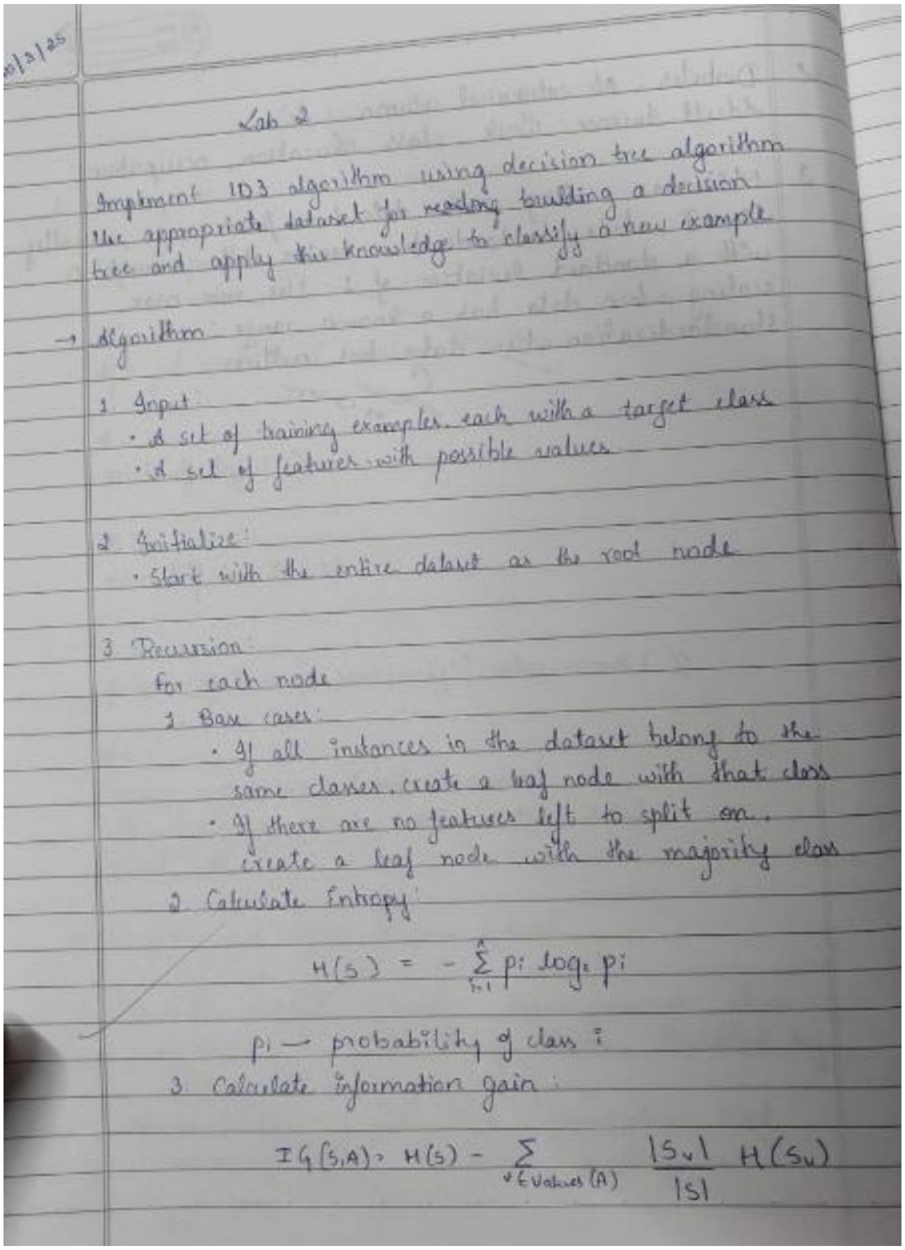
```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
logreg = LogisticRegression(max_iter=200, multi_class='multinomial', solver='lbfgs')
logreg.fit(X_train, y_train)

from sklearn.metrics import accuracy_score
y_pred = logreg.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Model Accuracy: {accuracy:.2f}")

from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=logreg.classes_)
disp.plot(cmap=plt.cm.Blues)
plt.title("Confusion Matrix for Zoo Animal Classification")
plt.show()

y_pred = logreg.predict(X_test)
pred_classes = [class_mapping[pred] for pred in y_pred]
print("Predicted Classes:", pred_classes)

import seaborn as sns
import matplotlib.pyplot as plt
sns.countplot(x='class_type', data=df)
plt.title("Class Distribution of Animals in Zoo Dataset")
plt.xlabel("Class Type")
plt.ylabel("Count")
plt.show()

from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
```

```
cm = confusion_matrix(y_test, y_pred)
class_labels = [class_mapping[num] for num in logreg.classes_]
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=class_labels)
disp.plot(cmap=plt.cm.Blues)
plt.title("Confusion Matrix with Class Names")
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

Implement ID3 algorithm using decision tree algorithm the appropriate dataset for ~~reading~~ building a decision tree and apply this knowledge to classify a new example

→ Algorithm

1. Input
   - A set of training examples each with a target class
   - A set of features with possible values

2. Initialize:
   - Start with the entire dataset as the root node

3. Recursion:

   For each node

   1. Base cases:
      - If all instances in the dataset belong to the same classes, create a leaf node with that class
      - If there are no features left to split on, create a leaf node with the majority class
   2. Calculate Entropy

$$H(S) = -\sum_{i=1}^{n} p_i \log_2 p_i$$

p_i — probability of class i

   3. Calculate information gain:

$$IG(S,A) = H(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} H(S_v)$$

↳ Select the feature with highest IG

4. Split the dataset
   - Recursively apply ID3 algorithm to the subset, treating it as a new dataset

5. Construct the tree
   - Repeat steps 3 and 4 recursively till no features are left

6. Output
   - A decision tree representing the learned classification model

Code:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score, recall_score, f1_score
from sklearn.preprocessing import LabelEncoder

def train_and_evaluate_iris():
    iris_df = pd.read_csv("iris.csv")
    X = iris_df.drop(columns=["species"])
    y = iris_df["species"]
    y_le = LabelEncoder()
    y = y_le.fit_transform(y)
```

```
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
    model = DecisionTreeClassifier(random_state=42)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    # Evaluating the model
    acc = accuracy_score(y_test, y_pred)
    prec = precision_score(y_test, y_pred, average='weighted')
    rec = recall_score(y_test, y_pred, average='weighted')
    f1 = f1_score(y_test, y_pred, average='weighted')
    cm = confusion_matrix(y_test, y_pred)

    print("IRIS Dataset Classification:")
    print(f"Accuracy Score: {acc:.4f}")
    print(f"Precision Score: {prec:.4f}")
    print(f"Recall Score: {rec:.4f}")
    print(f"F1 Score: {f1:.4f}")

    plt.figure(figsize=(6, 4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=y_le.classes_,
yticklabels=y_le.classes_)
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.title("Confusion Matrix: iris.csv")
    plt.show()

train_and_evaluate_iris()

def train_and_evaluate_drug():
    drug_df = pd.read_csv("drug.csv")
    categorical_features = ["Sex", "BP", "Cholesterol"]
    label_encoders = {}
```

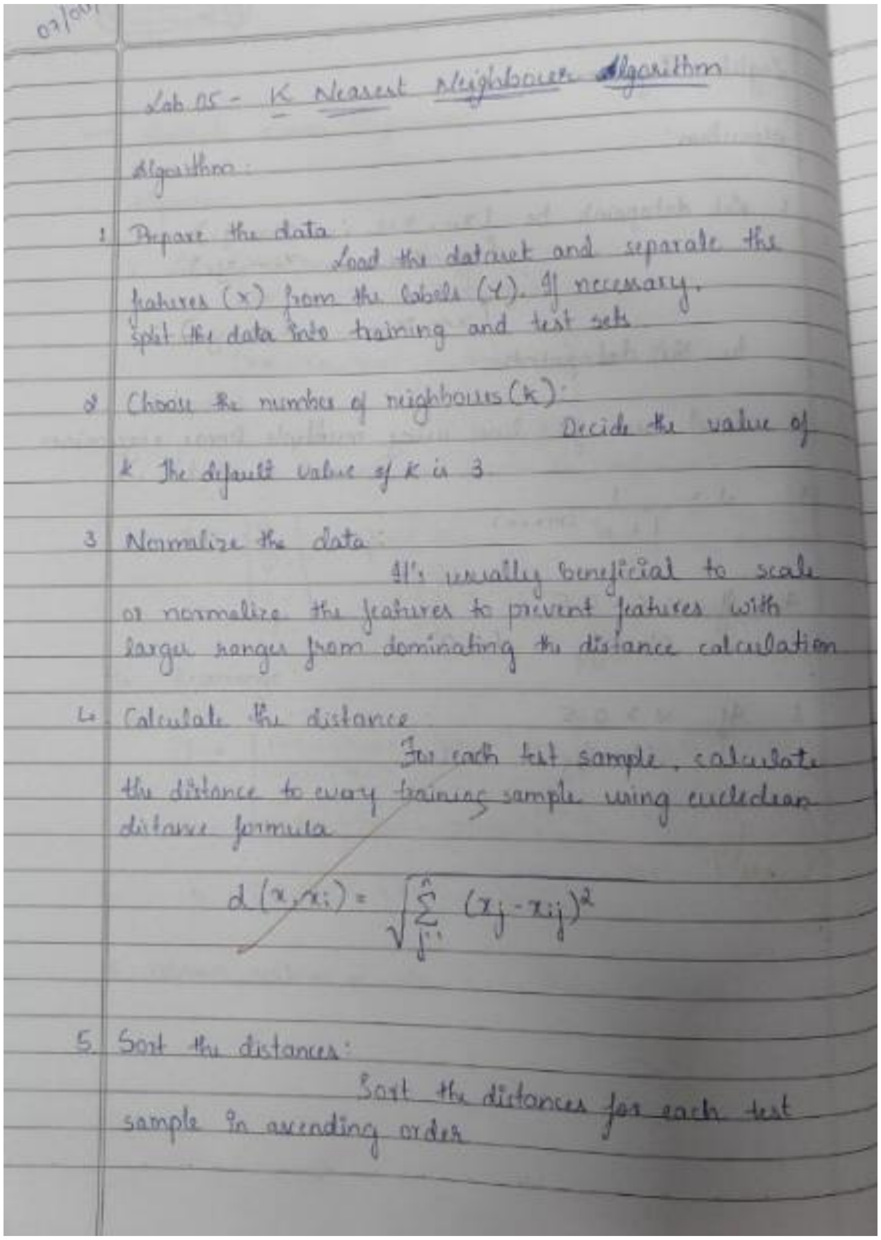
```
for col in categorical_features:
    le = LabelEncoder()
    drug_df[col] = le.fit_transform(drug_df[col])
    label_encoders[col] = le
X = drug_df.drop(columns=["Drug"])
y = drug_df["Drug"]
y_le = LabelEncoder()
y = y_le.fit_transform(y)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

model = DecisionTreeClassifier(random_state=42)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

acc = accuracy_score(y_test, y_pred)
prec = precision_score(y_test, y_pred, average='weighted')
rec = recall_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')
cm = confusion_matrix(y_test, y_pred)

print("Drug Dataset Classification:")
print(f"Accuracy Score: {acc:.4f}")
print(f"Precision Score: {prec:.4f}")
print(f"Recall Score: {rec:.4f}")
print(f"F1 Score: {f1:.4f}")

plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=y_le.classes_,
yticklabels=y_le.classes_)
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix: drug.csv")
```

```python
    plt.show()

train_and_evaluate_drug()

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.tree import DecisionTreeRegressor, plot_tree
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_absolute_error, mean_squared_error

petrol_df = pd.read_csv("petrol_consumption.csv")
X = petrol_df.drop(columns=["Petrol_Consumption"])
y = petrol_df["Petrol_Consumption"]
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
model = DecisionTreeRegressor(max_depth=5, random_state=42)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

print("Petrol Consumption Regression:")
print("Mean Absolute Error (MAE):", mean_absolute_error(y_test, y_pred))
print("Mean Squared Error (MSE):", mean_squared_error(y_test, y_pred))
print("Root Mean Squared Error (RMSE):", np.sqrt(mean_squared_error(y_test, y_pred)))
```

Program 6

Build KNN Classification model for a given dataset.

Screenshot:



07/04

Lab 05 - K Nearest Neighbour Algorithm

Algorithm:

1. Prepare the data: Load the dataset and separate the features (X) from the labels (Y). If necessary, split the data into training and test sets.

2. Choose the number of neighbours (k): Decide the value of k. The default value of k is 3.

3. Normalize the data: It's usually beneficial to scale or normalize the features to prevent features with larger ranges from dominating the distance calculation.

4. Calculate the distance: For each test sample, calculate the distance to every training sample using euclidean distance formula

$$d(x, x_i) = \sqrt{\sum_{j=1}^{n} (x_j - x_{ij})^2}$$

5. Sort the distances: Sort the distances for each test sample in ascending order

6. Select the K nearest neighbours
From the sorted distances, select the top k nearest neighbours.

7. Count the class labels of neighbours
For each test sample, count the class labels of k nearest neighbours

8. Determine the predicted class:
The predicted class is typically determined by the majority vote

9. Make the prediction
Assign the predicted class label to the test sample

10. Evaluate the model.
Evaluate the model using performance metrics like accuracy

Code:

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

iris_df = pd.read_csv('iris.csv')
```

```
le = LabelEncoder()
iris_df['species'] = le.fit_transform(iris_df['species'])
X = iris_df.drop('species', axis=1)
y = iris_df['species']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

error_rates = []
accuracies = []
k_values = range(1, 10)
for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    y_pred_k = knn.predict(X_test)
    error = 1 - accuracy_score(y_test, y_pred_k)
    error_rates.append(error)
    accuracies.append(accuracy_score(y_test, y_pred_k))

plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(k_values, accuracies, marker='o', color='blue')
plt.title("Accuracy vs K")
plt.xlabel("K Value")
plt.ylabel("Accuracy")

plt.subplot(1, 2, 2)
plt.plot(k_values, error_rates, marker='o', color='red')
plt.title("Error Rate vs K")
plt.xlabel("K Value")
plt.ylabel("Error Rate")
plt.tight_layout()
plt.show()
best_k = k_values[accuracies.index(max(accuracies))]
```

```
print(f"Best K: {best_k} with Accuracy: {max(accuracies):.2f}")

knn = KNeighborsClassifier(n_neighbors=best_k)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)

# Evaluation
print("\n=== Final Evaluation on IRIS Dataset ===")
print("Accuracy Score:", accuracy_score(y_test, y_pred))
print("\nClassification Report:")
print(classification_report(y_test, y_pred, labels=[0, 1, 2], target_names=le.classes_))

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=le.classes_, yticklabels=le.classes_)
plt.title("Confusion Matrix - IRIS")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

df = pd.read_csv('diabetes.csv')
X = df.drop('Outcome', axis=1)
y = df['Outcome']
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, random_state=42, stratify=y
)
accuracy_scores = []
k_range = range(1, 21)
```

```
for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    y_pred_k = knn.predict(X_test)
    acc = accuracy_score(y_test, y_pred_k)
    accuracy_scores.append(acc)

plt.figure(figsize=(8, 5))
plt.plot(k_range, accuracy_scores, marker='o', color='purple')
plt.title("Accuracy vs K (Diabetes Dataset)")
plt.xlabel("K Value")
plt.ylabel("Accuracy")
plt.xticks(k_range)
plt.grid()
plt.show()
best_k = k_range[accuracy_scores.index(max(accuracy_scores))]
print(f"Best K: {best_k} with Accuracy: {max(accuracy_scores):.2f}")

knn = KNeighborsClassifier(n_neighbors=best_k)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)

print("=== Final Evaluation (Diabetes Dataset) ===")
print("Accuracy Score:", accuracy_score(y_test, y_pred))
print("\nClassification Report:")
print(classification_report(y_test, y_pred))

cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Purples', xticklabels=['No Diabetes', 'Diabetes'],
yticklabels=['No Diabetes', 'Diabetes'])
plt.title("Confusion Matrix - Diabetes")
plt.xlabel("Predicted")
```

```
plt.ylabel("Actual")
plt.show()

heart_df = pd.read_csv('heart.csv')
X = heart_df.drop('target', axis=1)
y = heart_df['target']
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, random_state=42, stratify=y
)
accuracy_scores = []
k_range = range(1, 21)

for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    y_pred_k = knn.predict(X_test)
    acc = accuracy_score(y_test, y_pred_k)
    accuracy_scores.append(acc)

plt.figure(figsize=(8, 5))
plt.plot(k_range, accuracy_scores, marker='o', color='red')
plt.title("Accuracy vs K (Heart Dataset)")
plt.xlabel("K Value")
plt.ylabel("Accuracy")
plt.xticks(k_range)
plt.grid()
plt.show()

best_k = k_range[accuracy_scores.index(max(accuracy_scores))]
print(f"Best K: {best_k} with Accuracy: {max(accuracy_scores):.2f}")
```

```
knn = KNeighborsClassifier(n_neighbors=best_k)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)

print("=== Final Evaluation (Heart Dataset) ===")
print("\nAccuracy Score:", accuracy_score(y_test, y_pred))
print("\nClassification Report:")
print(classification_report(y_test, y_pred, target_names=['No Disease', 'Disease']))
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Reds', xticklabels=['No Disease', 'Disease'],
yticklabels=['No Disease', 'Disease'])
plt.title("Confusion Matrix - Heart Disease")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

Program 7

Build Support vector machine model for a given dataset.

Screenshot:

Support Vector Machine (SVM)

Algorithm:

1. Prepare the data:
   Load the dataset and separate the features (X) from the labels (Y)

2. Split dataset:
   Divide the data into training and testing sets in a specified ratio

3. Initialize the SVM class:
   C → Regularization constant
   max_iter → No of training iterations
   Kernel: linear
   $K(x, x') = x \cdot x'$

4. One vs Rest Training Strategy:
   For each class c in the set of unique classes:
   Convert labels into binary

   $$y\_binary = \begin{cases} 1 & \text{if } y = c \\ -1 & \text{otherwise} \end{cases}$$

   Train a binary SVM classifier using the simplified SMO algorithm.

5. Binary SVM training

   Initialize:
   $\alpha = 0,\ b = 0$
   For each training sample
   - Randomly select index $j \neq i$
   - Compute prediction errors E_i and E_j
   - Save old values α_i, α_j
   - Compute bounds L, H
     if $L == H$, continue
   - Compute
     $\eta = 2K(x_i, x_j) - K(x_i, x_i) - K(x_j, x_j)$
     if $\eta \geq 0$, skip update

- Update α_j

$$\alpha_j = \alpha_j + \frac{y_j (E_i - E_j)}{\eta}$$

- Clip α_j
- Update α_i
- Compute b, the bias term
- Store model for each class

6. Prediction Phase

Compute decision score:

$$f(x) = \sum_j \alpha_j y_j K(x_i, x_j) + b$$

Store the score

Predict the class with maximum decision score

7. Evaluation:

Calculate accuracy = $\frac{\text{No of correct predictions}}{\text{Total no of samples}} \times 100$

Code:

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix, roc_auc_score, roc_curve
from sklearn.preprocessing import label_binarize
import matplotlib.pyplot as plt
import seaborn as sns
```

```
iris = pd.read_csv("iris.csv")
label_encoder = LabelEncoder()
iris['species'] = label_encoder.fit_transform(iris['species'])
class_names_iris = label_encoder.classes_
X_iris = iris.drop('species', axis=1)
y_iris = iris['species']
X_train_iris, X_test_iris, y_train_iris, y_test_iris = train_test_split(X_iris, y_iris, test_size=0.2,
random_state=42)

scaler = StandardScaler()
X_train_iris = scaler.fit_transform(X_train_iris)
X_test_iris = scaler.transform(X_test_iris)
svm_linear = SVC(kernel='linear')
svm_linear.fit(X_train_iris, y_train_iris)
y_pred_linear = svm_linear.predict(X_test_iris)
acc_linear = accuracy_score(y_test_iris, y_pred_linear)
cm_linear = confusion_matrix(y_test_iris, y_pred_linear)

plt.figure(figsize=(6,4))
sns.heatmap(cm_linear, annot=True, fmt='d', cmap='Blues', xticklabels=class_names_iris,
yticklabels=class_names_iris)
plt.title(f'IRIS SVM Linear Kernel\nAccuracy: {acc_linear:.2f}')
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.tight_layout()
plt.show()

svm_rbf = SVC(kernel='rbf')
svm_rbf.fit(X_train_iris, y_train_iris)
y_pred_rbf = svm_rbf.predict(X_test_iris)
acc_rbf = accuracy_score(y_test_iris, y_pred_rbf)
cm_rbf = confusion_matrix(y_test_iris, y_pred_rbf)
```

```
plt.figure(figsize=(6,4))
sns.heatmap(cm_rbf, annot=True, fmt='d', cmap='Greens', xticklabels=class_names_iris,
yticklabels=class_names_iris)
plt.title(f'IRIS SVM RBF Kernel\nAccuracy: {acc_rbf:.2f}')
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.tight_layout()
plt.show()

letters = pd.read_csv("letter-recognition.csv")
X_letters = letters.drop('letter', axis=1)
y_letters = letters['letter']
label_encoder_letters = LabelEncoder()
y_letters_encoded = label_encoder_letters.fit_transform(y_letters)
class_names_letters = label_encoder_letters.classes_

X_train_letters, X_test_letters, y_train_letters, y_test_letters = train_test_split(
    X_letters, y_letters_encoded, test_size=0.2, random_state=42)

scaler_letters = StandardScaler()
X_train_letters = scaler_letters.fit_transform(X_train_letters)
X_test_letters = scaler_letters.transform(X_test_letters)
svm_letters = SVC(kernel='rbf', probability=True)
svm_letters.fit(X_train_letters, y_train_letters)

y_pred_letters = svm_letters.predict(X_test_letters)
acc_letters = accuracy_score(y_test_letters, y_pred_letters)
cm_letters = confusion_matrix(y_test_letters, y_pred_letters)

plt.figure(figsize=(14, 12))
sns.heatmap(cm_letters, annot=True, fmt='d', cmap='Purples',
```

```
            xticklabels=class_names_letters,
            yticklabels=class_names_letters,
            annot_kws={"size": 8},
            cbar=True)
plt.title(f'Letter Recognition - SVM RBF Kernel\nAccuracy: {acc_letters*100:.2f}%', fontsize=16)
plt.xlabel("Predicted Label", fontsize=14)
plt.ylabel("True Label", fontsize=14)
plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.tight_layout()
plt.show()

y_test_binarized = label_binarize(y_test_letters, classes=np.arange(len(class_names_letters)))
y_score = svm_letters.predict_proba(X_test_letters)
auc_score = roc_auc_score(y_test_binarized, y_score, average='macro')
fpr = dict()
tpr = dict()
for i in range(len(class_names_letters)):
    fpr[i], tpr[i], _ = roc_curve(y_test_binarized[:, i], y_score[:, i])
plt.figure(figsize=(8, 6))
for i in range(0, len(class_names_letters), 4): # Plot every 4th class
    plt.plot(fpr[i], tpr[i], lw=1.5, label=f'Class {class_names_letters[i]}')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title(f"Multi-Class ROC Curve (Macro AUC = {auc_score:.6f})")
plt.legend(loc="lower right", fontsize='small')
plt.grid()
plt.tight_layout()
plt.show()

print(f"Exact AUC Score = {auc_score}")
```

Program 8

Implement Random forest ensemble method on a given dataset.

Screenshot:

Lab 06 - Random Forest

Algorithm:

1. Data Preparation:
   Given a dataset D with N samples and M features, $D = \{(x_1, y_1), (x_2, y_2) \ldots (x_N, y_N)\}$, where x_i represents the features and y_i represents the target variable for the i^{th} sample.

2. Bootstrap Sampling:
   For each tree in the forest, draw a bootstrap sample from the dataset D by sampling N instances with replacement.

3. Random feature subset selection:
   For each split, randomly select a subset of m features from the M total features. Typically, $m = \sqrt{M}$ for classification. At each node, the best feature to split on is chosen based on some criterion.

4. Build Decision Trees:
   ~~For each tree b, build a decision tree T^b using the bootstrap sample D^b and the random feature subset f subset. Recursively split the data at each node by selecting the feature and threshold that minimize the chosen splitting criterion~~

5. Calculate Impurity:
For classification, compute Gini Impurity for each possible split of the dataset

6. Calculate Mean Squared Error:
For regression, calculate mean squared error for each node

7. Recursive Splitting:
Recursively splitting the data at each node of the three based on the feature that provides the best split according to the impurity or MSE

8. Repeat for Multiple Trees:
Repeat steps 2 to 7 B times to construct Random forest

9. Make Predictions
Classification: Majority vote
Regression: Average

10. Evaluate the model:
Classification: Accuracy
Regression: MSE, MAE

Code:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import confusion_matrix
```

```
iris_df = pd.read_csv("iris.csv")
X = iris_df.drop('species', axis=1)
y = iris_df['species']
le = LabelEncoder()
y_encoded = le.fit_transform(y)

X_train, X_test, y_train, y_test = train_test_split(X, y_encoded, test_size=0.3, random_state=42)
rf_model = RandomForestClassifier(n_estimators=10, random_state=42)
rf_model.fit(X_train, y_train)
y_pred = rf_model.predict(X_test)
print("Random Forest Accuracy with 10 trees:", accuracy_score(y_test, y_pred))

scores = []
n_range = range(1, 101)
best_model = None
best_preds = None

for n in n_range:
    model = RandomForestClassifier(n_estimators=n, random_state=42)
    model.fit(X_train, y_train)
    preds = model.predict(X_test)
    acc = accuracy_score(y_test, preds)
    scores.append(acc)
    if acc == max(scores):
        best_model = model
        best_preds = preds

best_score = max(scores)
best_n = n_range[scores.index(best_score)]
print(f"Best Random Forest Accuracy: {best_score:.4f} with {best_n} trees")
```

```
plt.figure(figsize=(10, 5))
plt.plot(n_range, scores, marker='o', linestyle='-', color='blue')
plt.title('Random Forest Accuracy vs Number of Trees (Iris Dataset)')
plt.xlabel('Number of Trees')
plt.ylabel('Accuracy')
plt.grid(True)
plt.show()

cm = confusion_matrix(y_test, best_preds)
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=le.classes_, yticklabels=le.classes_)
plt.title(f"Confusion Matrix for Best Random Forest Model ({best_n} Trees)")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

Program 9

Implement Boosting ensemble method on a given dataset.

Screenshot:

Boosting Ensemble Method

Algorithm

1 Load the dataset
Given dataset $D = \{(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)\}$, where $y_i \in \{-1, +1\}$ for binary classification.

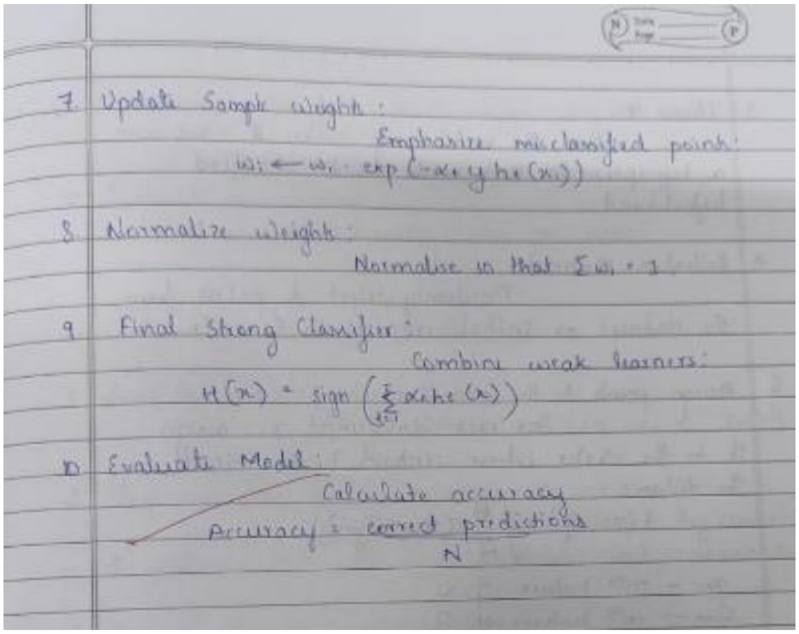
2 Initialize sample weights:
Assign equal weights to each datapoint:
$$w_i = \frac{1}{N}$$

3 Choose Number of Iterations T:
Set the number of base learners T

4 For t - 1, Train Weak Learner:
Train a weak learner $h_t(x)$ on weighted data.

5 Calculate Error of Weak Learner:
Weighted classification error:
$$\epsilon_t = \sum_{i=1}^{N} w_i \cdot 1 (h_t(x_i) \neq y_i)$$

6 Compute Learner's Weight:
Learner importance:
$$\alpha_t = \frac{1}{2} \ln \left(\frac{1 - \epsilon_t}{\epsilon_t} \right)$$



7. Update Sample weights:

Emphasize misclassified points:

$w_i \leftarrow w_i \cdot \exp(-\alpha_t y_i h_t(x_i))$

8. Normalize weights:

Normalise so that $\sum w_i = 1$

9. Final Strong Classifier:

Combine weak learners:

$H(x) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)$

10. Evaluate Model:

Calculate accuracy

$\text{Accuracy} = \frac{\text{correct predictions}}{N}$

Code:

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

income_df = pd.read_csv("income.csv")
X_income = income_df.drop('income_level', axis=1)
y_income = income_df['income_level']
X_train_i, X_test_i, y_train_i, y_test_i = train_test_split(X_income, y_income, test_size=0.3,
random_state=42)

ada_model = AdaBoostClassifier(n_estimators=10, random_state=42)
ada_model.fit(X_train_i, y_train_i)
```

```
y_pred_i = ada_model.predict(X_test_i)
print("AdaBoost Accuracy with 10 estimators:", accuracy_score(y_test_i, y_pred_i))

scores_ada = []
n_range_ada = range(1, 51)
best_model_ada = None
best_preds_ada = None

for n in n_range_ada:
    model = AdaBoostClassifier(n_estimators=n, random_state=42)
    model.fit(X_train_i, y_train_i)
    preds = model.predict(X_test_i)
    acc = accuracy_score(y_test_i, preds)
    scores_ada.append(acc)
    if acc == max(scores_ada):
        best_model_ada = model
        best_preds_ada = preds

best_score_ada = max(scores_ada)
best_n_ada = n_range_ada[scores_ada.index(best_score_ada)]
print(f"Best AdaBoost Accuracy: {best_score_ada:.4f} with {best_n_ada} estimators")

plt.figure(figsize=(10, 5))
plt.plot(n_range_ada, scores_ada, marker='o', linestyle='-', color='orange')
plt.title('AdaBoost Accuracy vs Number of Estimators (Income Dataset)')
plt.xlabel('Number of Estimators')
plt.ylabel('Accuracy')
plt.grid(True)
plt.show()

cm_ada = confusion_matrix(y_test_i, best_preds_ada)
plt.figure(figsize=(6, 5))
```

```
sns.heatmap(cm_ada, annot=True, fmt='d', cmap='Oranges', xticklabels=[0, 1], yticklabels=[0, 1])
plt.title(f"Confusion Matrix for Best AdaBoost Model ({best_n_ada} Estimators)")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

Program 10

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

Screenshot:

K-Means Clustering

Algorithm

1. Load the dataset:
Load the dataset from a CSV file into a pandas Dataframe
$D = \{(x_1, x_2 \ldots x_m)\}$ $x_i \in \mathbb{R}^m$

2. Preprocess the Data:
Handle missing values, normalize, standardize features, and extract the features X for clustering

3 Choose k

Select the number of cluster K. This is a hyperparameter that needs to be specified beforehand.

4 Initialize Centroids:

Randomly select k points from the dataset as initial centroids $C_1, C_2 \ldots C_K$

5. Assign points to the nearest cluster:

For each datapoint x_i, assign it to the cluster whose centroid is the closest. The distance:

$$d(x_i, C_j) = \sqrt{\sum_{m=1}^{M} (x_{im} - C_{jm})^2}$$

$x_{im} \rightarrow m^{th}$ feature of x_i

$C_{jm} \rightarrow m^{th}$ feature of C_j

6. Update Centroids:

After assigning all points to clusters, calculate the new centroids by taking mean of all points

7. Check for convergence:

If centroids do not change significantly, stop the algorithm

8. Repeat steps 5 to 7.

9. Assign final clusters:

Once convergence is reached, the final cluster assignments and centroids are obtained

10 Evaluate the clusters:

Sum of squared errors, silhouette score

Code:

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

df1=pd.read_csv("iris.csv")
df1.head()
df = df1.drop(['sepal_length','sepal_width','species'],axis=1)
scaler = StandardScaler()
scaled_df = scaler.fit_transform(df)
wcss = []
for i in range(1, 11):
kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10, random_state=0)
kmeans.fit(scaled_df)
wcss.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()

kmeans = KMeans(n_clusters=3, init='k-means++', max_iter=300, n_init=10, random_state=0)
pred_y = kmeans.fit_predict(scaled_df)
df['cluster'] = pred_y
```

```
plt.scatter(df['petal_length'], df['petal_width'], c=df['cluster'])
plt.title('Clusters of Iris Flowers')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
plt.show()
```

Program 11

Implement Dimensionality reduction using Principal Component Analysis (PCA) method.

Screenshot:

Principle Component Analysis

1. Load the dataset:

Load the dataset $D = \{(x_1, x_2, x \ldots x_n)\}$

2. Preprocess the data:

Standardize the dataset by centering the features and scale them to have unit variance.

3. Compute the covariance matrix:

Compute covariance matrix Σ of the standardized data:

$$\Sigma = \frac{1}{N-1} X^T X$$

4. Compute Eigenvalues and Eigenvectors:

Find eigenvalues & eigenvectors of the covariance matrix Σ.

$$\Sigma v = \lambda v$$

5. Sort Eigenvalues & Eigenvectors:

Sort the eigenvalues $\lambda_1, \lambda_2, \ldots \lambda_m$ in descending order. Sort the eigenvectors correspondingly

6. Select Top k Eigenvectors: Select the top k eigenvectors to reduce the dimensionality to k dimensions

7. Construct the Projection Matrix: W_k using top k eigenvectors. Shape = $M \times k$

8. Project Data onto new space:

$$X_{PCA} = X \cdot W_k$$

X_{PCA} = Reduced dataset.

9. Reconstruct Data:

$$X_{re} = X_{PCA} \cdot W_k^T$$

10. Evaluate the results:

$$\text{Variance Ratio} = \frac{\lambda_k}{\sum_{i=1}^{M} \lambda_i}$$

Code:

```
from google.colab import files
heart=files.upload()
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
```

```
from scipy import stats
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.decomposition import PCA

df1=pd.read_csv("heart.csv")
df1.head()
text_cols = df1.select_dtypes(include=['object']).columns
label_encoder = LabelEncoder()
for col in text_cols:
df1[col] = label_encoder.fit_transform(df1[col])
print(df1.head())
X = df1.drop('HeartDisease', axis=1)
y = df1['HeartDisease']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Support Vector Machine
svm_model = SVC(kernel='linear', random_state=42)
svm_model.fit(X_train, y_train)
svm_predictions = svm_model.predict(X_test)
svm_accuracy = accuracy_score(y_test, svm_predictions)
print(f"SVM Accuracy: {svm_accuracy}")
```

```
# Logistic Regression
lr_model = LogisticRegression(random_state=42)
lr_model.fit(X_train, y_train)
lr_predictions = lr_model.predict(X_test)
lr_accuracy = accuracy_score(y_test, lr_predictions)
print(f"Logistic Regression Accuracy: {lr_accuracy}")

# Random Forest
rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_train, y_train)
rf_predictions = rf_model.predict(X_test)
rf_accuracy = accuracy_score(y_test, rf_predictions)
print(f"Random Forest Accuracy: {rf_accuracy}")

models = {
"SVM": svm_accuracy,
"Logistic Regression": lr_accuracy,
"Random Forest": rf_accuracy}
best_model = max(models, key=models.get)
print(f"\nBest Model: {best_model} with accuracy {models[best_model]}")

pca = PCA(n_components=0.95)
X_train_pca = pca.fit_transform(X_train)
X_test_pca = pca.transform(X_test)
svm_model_pca = SVC(kernel='linear', random_state=42)
svm_model_pca.fit(X_train_pca, y_train)
svm_predictions_pca = svm_model_pca.predict(X_test_pca)
svm_accuracy_pca = accuracy_score(y_test, svm_predictions_pca)
print(f"SVM Accuracy (with PCA): {svm_accuracy_pca}")

lr_model_pca = LogisticRegression(random_state=42)
```

```
lr_model_pca.fit(X_train_pca, y_train)
lr_predictions_pca = lr_model_pca.predict(X_test_pca)
lr_accuracy_pca = accuracy_score(y_test, lr_predictions_pca)
print(f"Logistic Regression Accuracy (with PCA): {lr_accuracy_pca}")

rf_model_pca = RandomForestClassifier(random_state=42)
rf_model_pca.fit(X_train_pca, y_train)
rf_predictions_pca = rf_model_pca.predict(X_test_pca)
rf_accuracy_pca = accuracy_score(y_test, rf_predictions_pca)
print(f"Random Forest Accuracy (with PCA): {rf_accuracy_pca}")

models_pca = {
"SVM": svm_accuracy_pca,
"Logistic Regression": lr_accuracy_pca,
"Random Forest": rf_accuracy_pca}
best_model_pca = max(models_pca, key=models_pca.get)
print(f"\nBest Model (with PCA): {best_model_pca} with accuracy {models_pca[best_model_pca]}")
```