VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
on

Machine Learning (23CS6PCMAL)

Submitted by

P Manya (1BM22CS187)

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 **P Manya (1BM22CS187),** 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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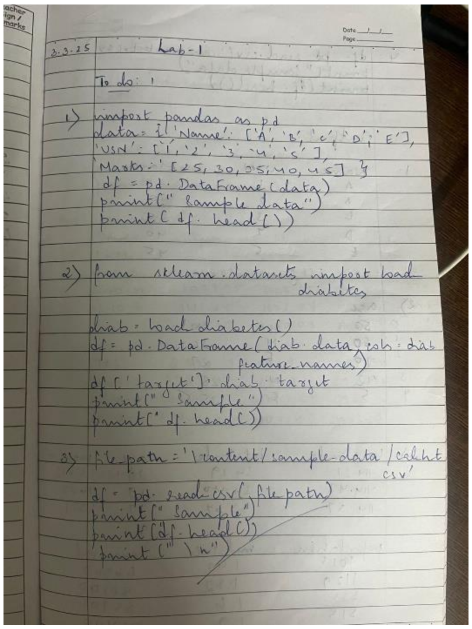
Index

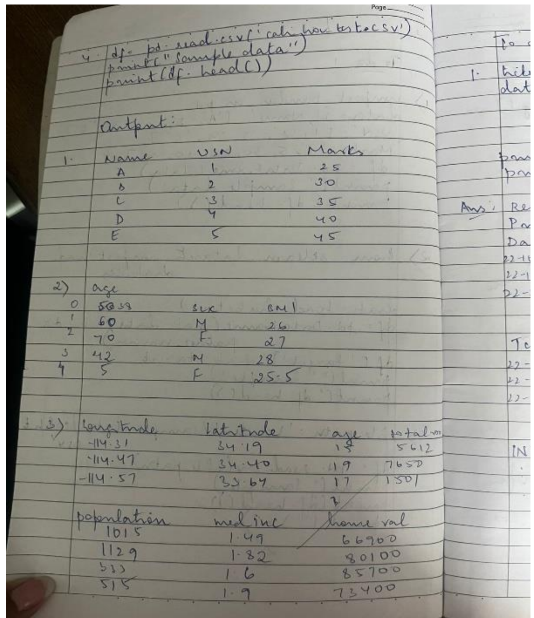
Github Link: https://github.com/pmanya6/ML_LAB/tree/main

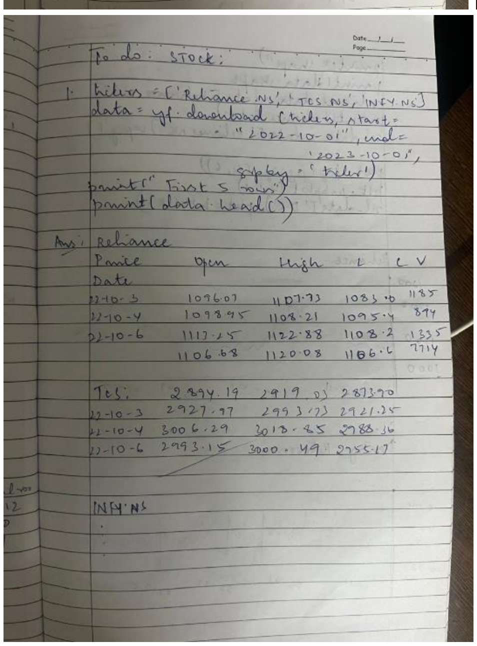
Program 1

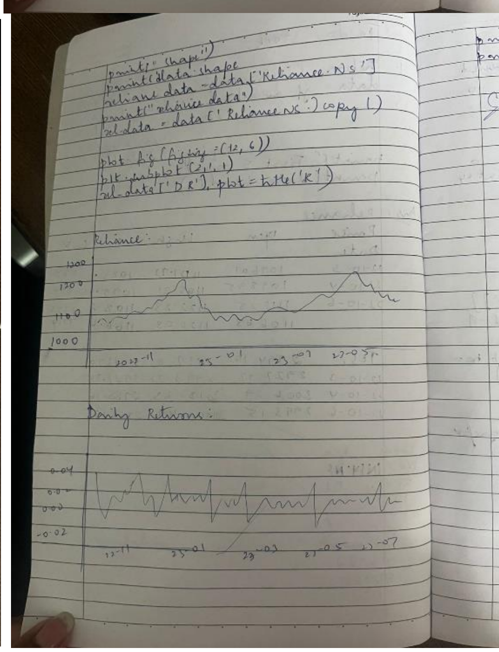
Write a python program to import and export data using Pandas library functions.

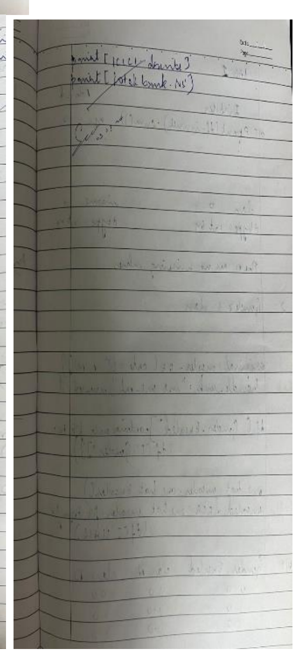
Screenshot:











Code:

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

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)
```

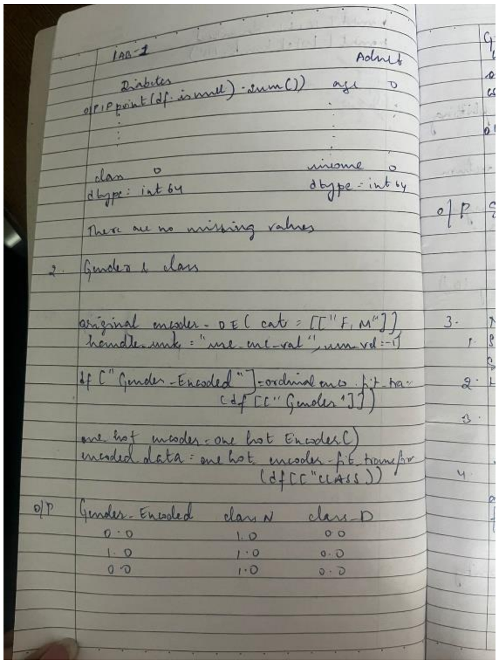
```
print("\nBest-selling products by quantity:")
print(best_selling_products)
sales_by_region.to_csv('sales_by_region.csv')
best_selling_products.to_csv('best_selling_products.csv')
print("Data saved to sales_by_region.csv and best_selling_products.csv")

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

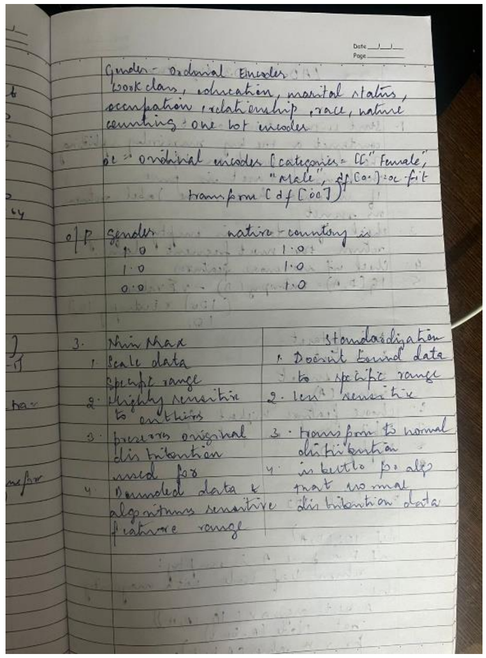
Demonstrate various data pre-processing techniques for a given dataset.

Screenshot:



LAB-2
Diabetes
Adult
o/p print(df.isnull().sum())
age 0
class 0
income 0
dtype: int64
dtype: int64
There are no missing values
2. Gender & class
original encoder = OE(cat = [["F, M"]], handle_unk = "use_enc_val", unk_val = -1)
df["Gender_Encoded"] = ordinal enc.fit_transform(df[["Gender"]])
one hot encoder = one hot Encoder()
encoded data = one hot encoder.fit_transform(df[["CLASS"]])

o/p Gender_Encoded	class_N	class_D
0.0	1.0	0.0
1.0	1.0	0.0
0.0	1.0	0.0



Gender - ordinal Encoder
work class, education, marital status, occupation, relationship, race, native country - one hot encoder
oe = ordinal encoder (categories = [["Female", "Male"]], df[0].oe.fit_transform(df[0]))

o/p Gender	native-country
0.0	1.0
1.0	1.0
0.0	1.0

3. Min Max	Standardization
1. Scale data specific range	1. Doesn't bound data to specific range
2. Highly sensitive to outliers	2. less sensitive
3. preserves original distribution	3. transform to normal distribution
4. used for bounded data & algorithms sensitive feature range	4. is better for algos that normal distribution data

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 '?':")
```

```python
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:")
```

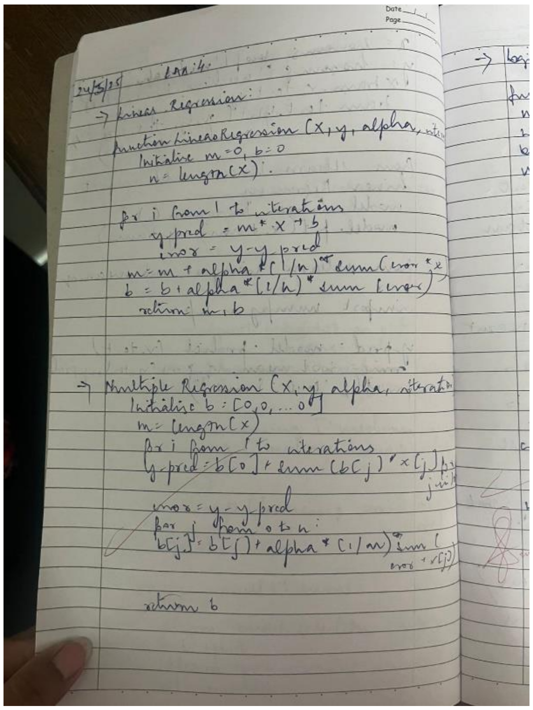
```
print(adult_df.head())

#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:



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
```

```python
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):
```

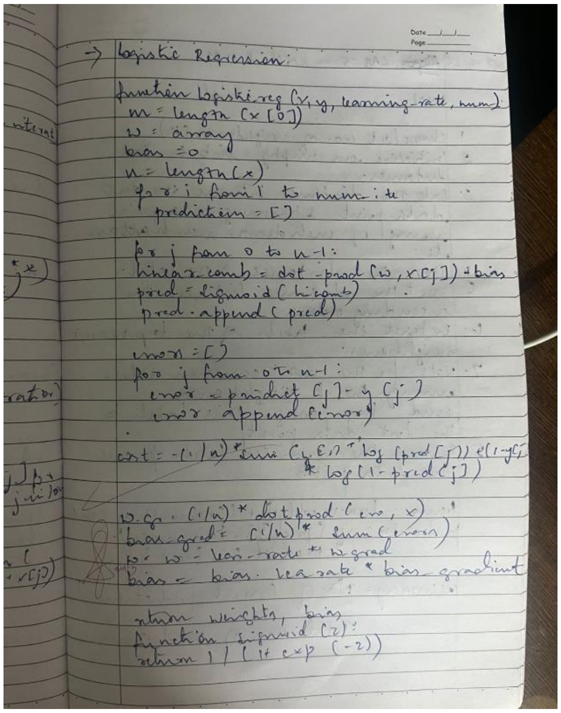
```
    word_to_num = {
        'zero': 0, 'one': 1, 'two': 2, 'three': 3, 'four': 4, 'five': 5,
        'six': 6, 'seven': 7, 'eight': 8, 'nine': 9, 'ten': 10,
        'eleven': 11, 'twelve': 12, 'thirteen': 13, 'fourteen': 14,
        'fifteen': 15
    }
    return word_to_num.get(value.lower(), value)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

<u>Program 4</u>

Build Logistic Regression Model for a given dataset.

Screenshot:



→ Logistic Regression:

```
function logistic_reg (x, y, learning_rate, num):
 m = length (x [0])
 w = array
 bias = 0
 n = length (x)
 for i from 1 to num_ite
   prediction = []

 for j from 0 to n-1:
 linear_comb = dot_prod (w, x[j]) + bias
 pred = sigmoid (li_comb)
 pred.append (pred)

 error = []
 for j from 0 to n-1:
   error = predict [j] - y [j]
   error.append (error)

cost = -(1/n) * sum (y[i] * log (pred [j]) + (1-y[j]
                  * log (1 - pred [j])

w_gr = (1/n) * dot_prod (error, x)
bias_grad = (1/n) * sum (errors)
w = w - lear_rate * w_grad
bias = bias - lea_rate * bias_gradient

return weights, bias
function sigmoid (z):
return 1 / (1 + exp (-z))
```

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()
```

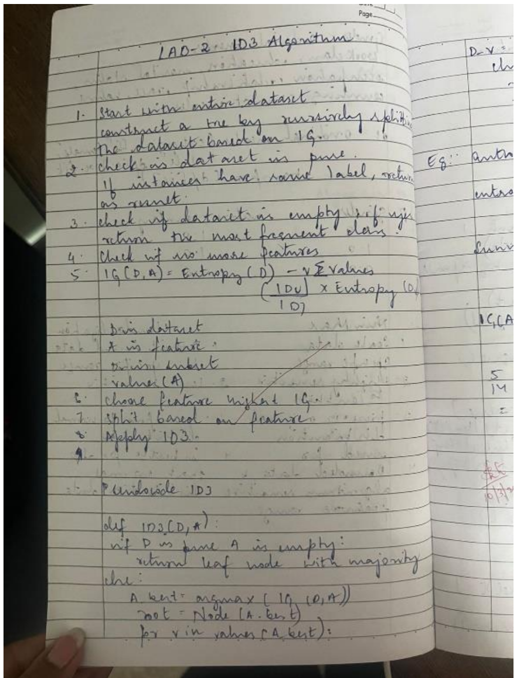
```python
plt.figure(figsize=(8, 6))
sns.countplot(x='salary', hue='left', data=df)
plt.title("Impact of Salary on Employee Retention")
plt.xlabel("Salary Level")
plt.ylabel("Employee Count")
plt.show()

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:



LAB-2 ID3 Algorithm

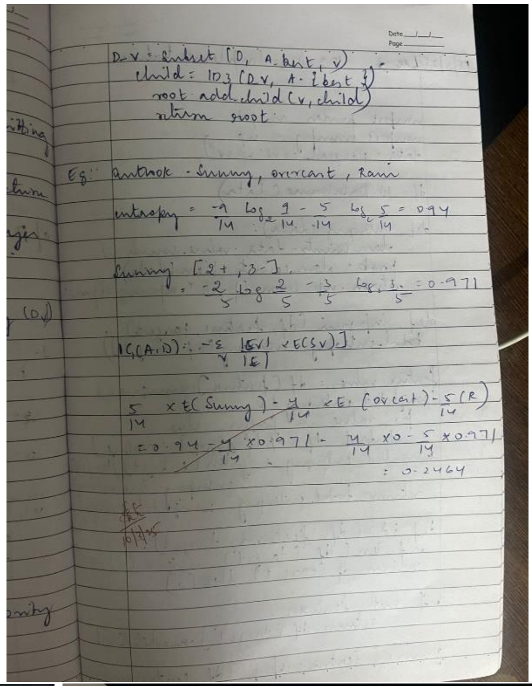
1. Start with entire dataset construct a tree by recursively splitting the dataset based on IG.
2. check if dataset is pure if instances have same label, return as result
3. check if dataset is empty if yes return the most frequent class
4. Check if no more features
5. IG(D,A) = Entropy(D) − v Σ values (|Dv| / |D|) × Entropy(Dv)

D is dataset
A is feature
Dv is subset
values(A)

6. choose feature highest IG.
7. split based on feature
8. Apply ID3.

Pseudocode ID3

```
def ID3(D,A):
  if D is pure A is empty:
    return leaf node with majority
  else:
    A_best = argmax(IG(D,A))
    root = Node(A_best)
    for v in values(A_best):
```



```
      Dv = subset(D, A_best, v)
      child = ID3(Dv, A - {best})
      root.add_child(v, child)
    return root
```

Eg: outlook - Sunny, overcast, Rain

entropy = −9/14 log₂ 9/14 − 5/14 log₂ 5/14 = 0.94

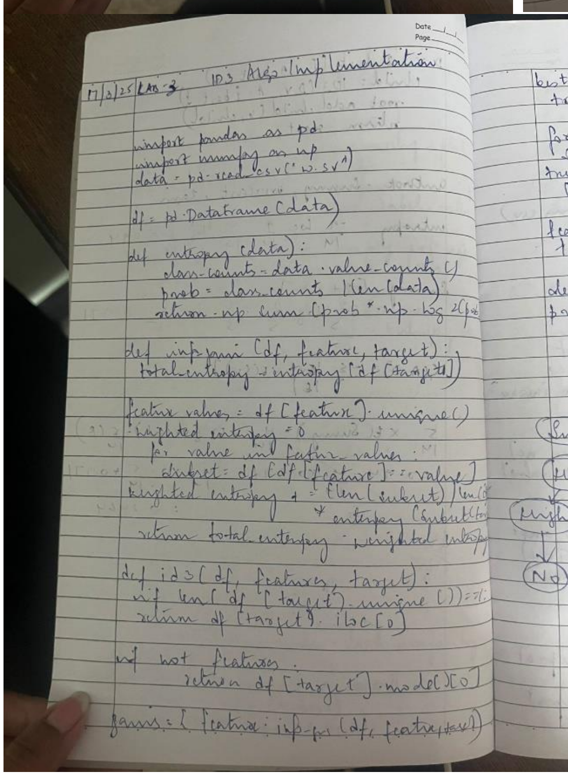
Sunny [2+, 3−] = −2/5 log 2/5 − 3/5 log 3/5 = 0.971

IG(A,D) = −Σ |Sv|/|S| × E(Sv)

5/14 × E(Sunny) − 4/14 × E(overcast) − 5/14 E(R)

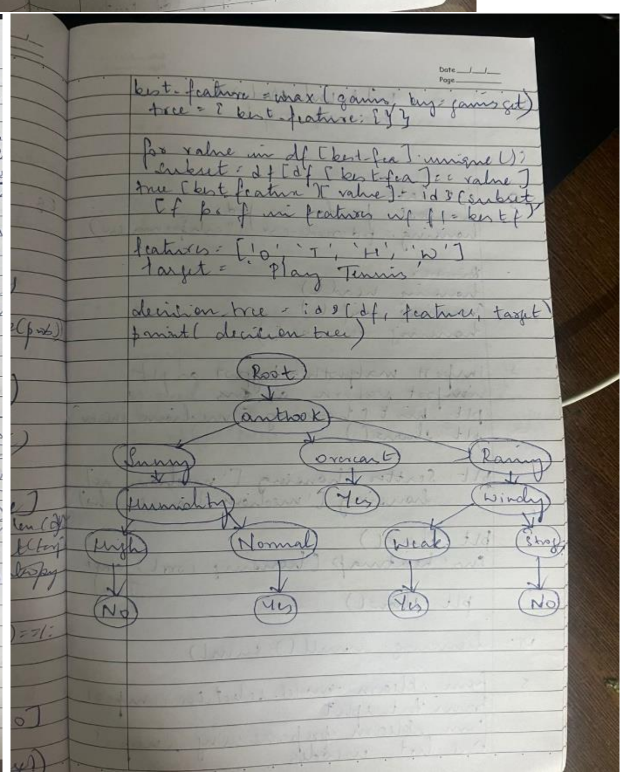
= 0.94 − 5/14 × 0.971 − 4/14 × 0 − 5/14 × 0.971

= 0.2464



17/3/25 LAB-3 ID3 Algo Implementation

```
import pandas as pd
import numpy as np
data = pd.read_csv('w.csv')

df = pd.DataFrame(data)

def entropy(data):
    class_counts = data.value_counts()
    prob = class_counts / len(data)
    return -np.sum(prob * np.log2(prob))

def info_gain(df, feature, target):
    total_entropy = entropy(df[target])

    feature_values = df[feature].unique()
    weighted_entropy = 0
    for value in feature_values:
        subset = df[df[feature] == value]
        weighted_entropy += (len(subset)/len(df)) * entropy(subset[target])
    return total_entropy - weighted_entropy

def id3(df, features, target):
    if len(df[target].unique()) == 1:
        return df[target].iloc[0]

    if not features:
        return df[target].mode()[0]

    gains = {feature: info_gain(df, feature, target)
```



```
    best_feature = max(gains, key=gains.get)
    tree = {best_feature: {}}

    for value in df[best_fea].unique():
        subset = df[df[best_fea] == value]
        tree[best_feature][value] = id3(subset,
            [f for f in features if f != best_f])

features = ['O', 'T', 'H', 'W']
target = 'Play Tennis'

decision_tree = id3(df, features, target)
print(decision_tree)
```

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')
```

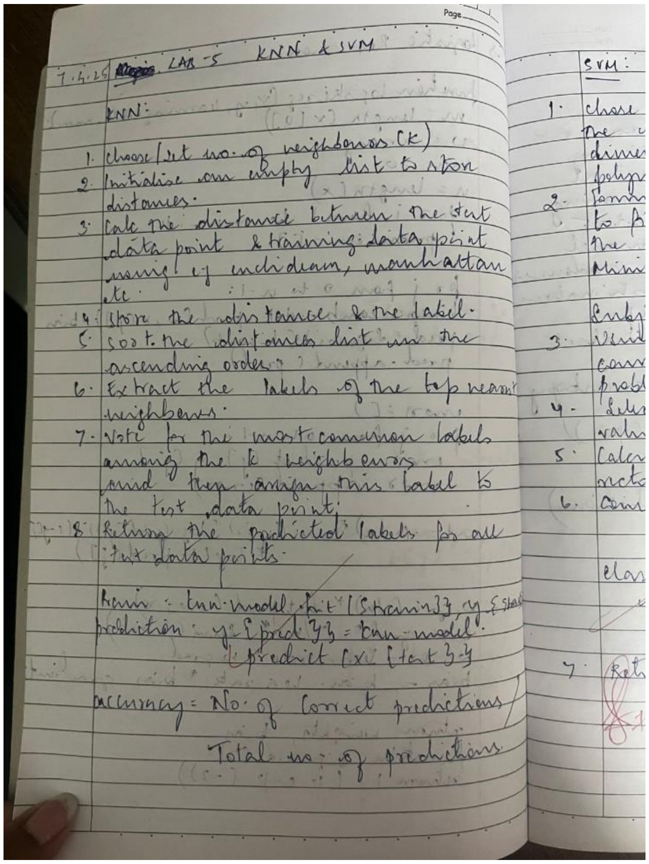
```
    rec = recall_score(y_test, y_pred, average='weighted')
    f1 = f1_score(y_test, y_pred, average='weighted')
    cm = confusion_matrix(y_test, y_pred)

    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")
    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:



7.4.25 LAB-5 KNN & SVM

KNN:

1. choose / set no. of neighbours (k)
2. Initialise an empty list to store distances.
3. calc the distance between the test data point & training data point using eg euclidean, manhattan etc.
4. store the distance & the label.
5. sort the distances list in the ascending order.
6. Extract the labels of the top nearest neighbours.
7. vote for the most common labels among the k neighbours and then assign this label to the test data point.
8. Return the predicted labels for all test data points.

train : knn.model.fit (S{train}}, y {S{train}}
prediction : y{pred}} = knn.model.predict (x {test}})

accuracy = No. of correct predictions / Total no. of predictions

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()
```

```python
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")
```

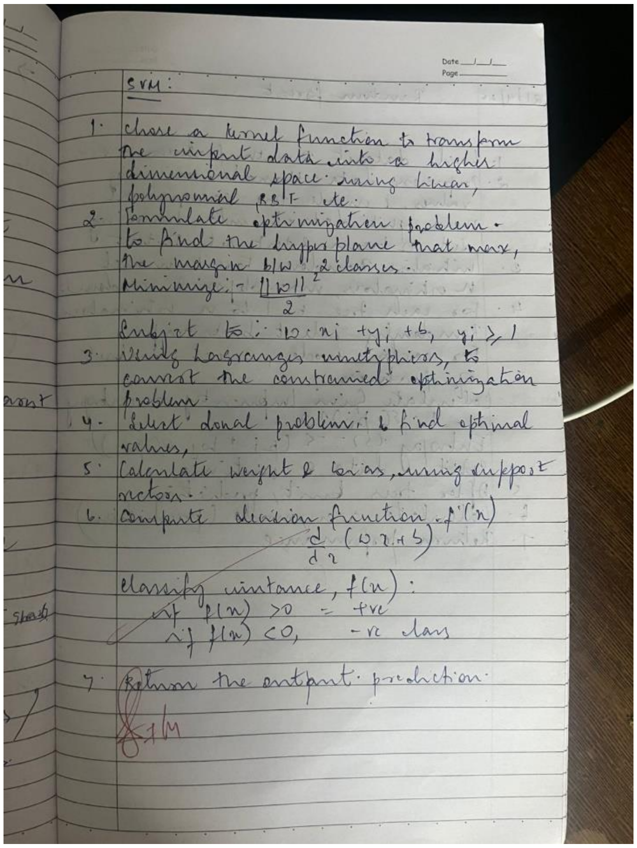
```
plt.show()

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}")
```

```python
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:



SVM:

1. chose a kernel function to transform the input data into a higher dimensional space using linear, polynomial, RBF etc.
2. Formulate optimization problem to find the hyperplane that max, the margin b/w 2 classes.
   Minimize:- $\frac{||w||^2}{2}$
   Subject to: $w \cdot x_i + y_i + b,\ y_i \geq 1$
3. Using Lagranges multipliers, to convert the constrained optimization problem.
4. Select dual problem & find optimal values,
5. Calculate weight & bias, using support vector.
6. Compute decision function $f'(x)$
   $\frac{d}{dx}(w.x+b)$
   classify instance, $f(x)$:
   if $f(x) > 0$ = +ve
   if $f(x) < 0$, -ve class
7. Return the output prediction.

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',
```

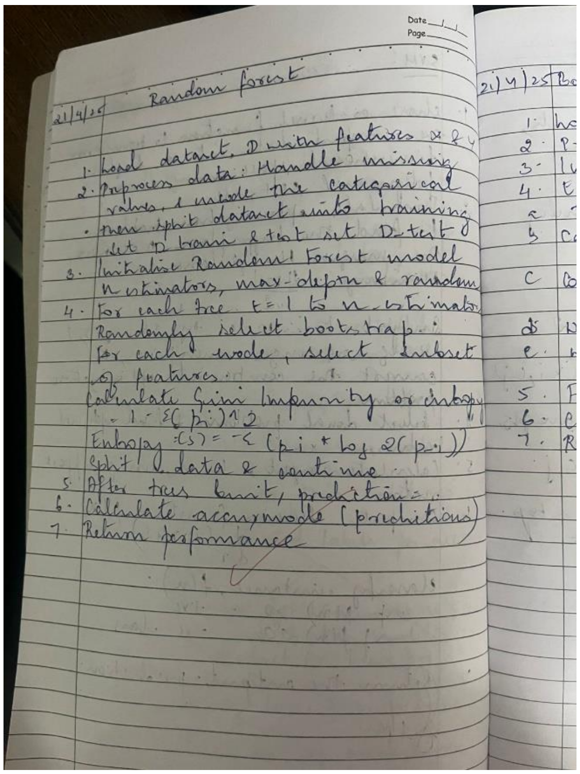
```
            xticklabels=class_names_letters,
            yticklabels=class_names_letters,
            annot_kws={"size": 8},
            cbar=True)
plt.title(f'Letter Recognition - SVM RBF Kernel\nAccuracy: {acc_letters*100:.2f}%', fontsize=16)
plt.xlabel("Predicted Label", fontsize=14)
plt.ylabel("True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


Random forest
21/4/25
1. Load dataset D with features x & y
2. Preprocess data: Handle missing values, encode the categorical
• then split dataset into training set D train & test set D test
3. Initialise Random Forest model n estimators, max depth & random
4. For each tree t = 1 to n estimators
Randomly select bootstrap.
For each node, select subset of features.
Calculate Gini Impurity or entropy
1 - Σ(pi)^2
Entropy(S) = -Σ(pi * log2(pi))
Split data & continue
5. After trees built, predictions
6. Calculate accuracy mode (predictions)
7. Return performance

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)
```

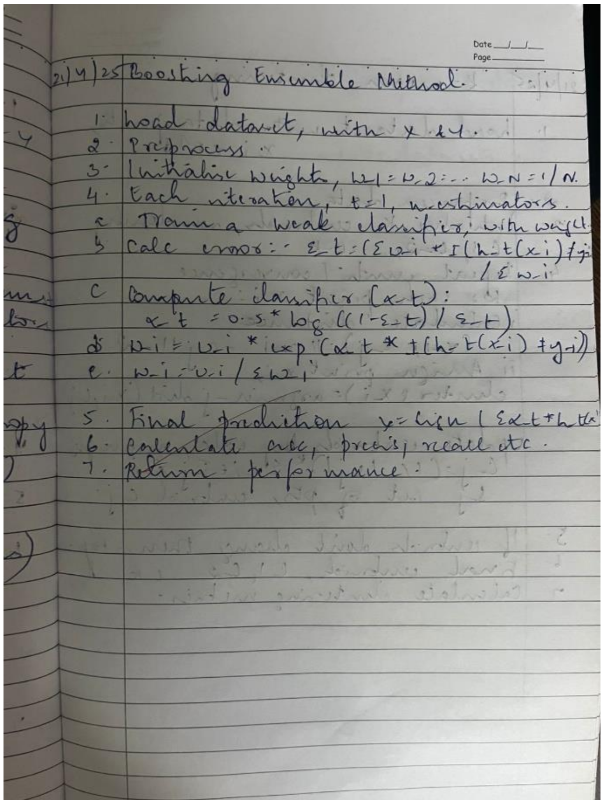
```python
y = iris_df['species']
le = LabelEncoder()
y_encoded = le.fit_transform(y)

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:



21/4/25 Boosting Ensemble Method.

1. Load dataset, with X & Y.
2. Preprocess.
3. Initialise weights, $w_1 = w_2 = \dots w_N = 1/N$.
4. Each iteration, t=1, n_estimators.
   a. Train a weak classifier, with weight
   b. Calc error: $\varepsilon_t = (\Sigma w_i * I(h_t(x_i) \neq y_i) / \Sigma w_i$
   c. Compute classifier (α_t):
   $\alpha_t = 0.5 * \log((1-\varepsilon_t)/\varepsilon_t)$
   d. $w_i = w_i * \exp(\alpha_t * I(h_t(x_i) \neq y_i))$
   e. $w_i = w_i / \Sigma w_i$
5. Final prediction $y = \text{sign}(\Sigma \alpha_t * h_t(x))$
6. Calculate acc, precis, recall etc.
7. Return performance.

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']
```

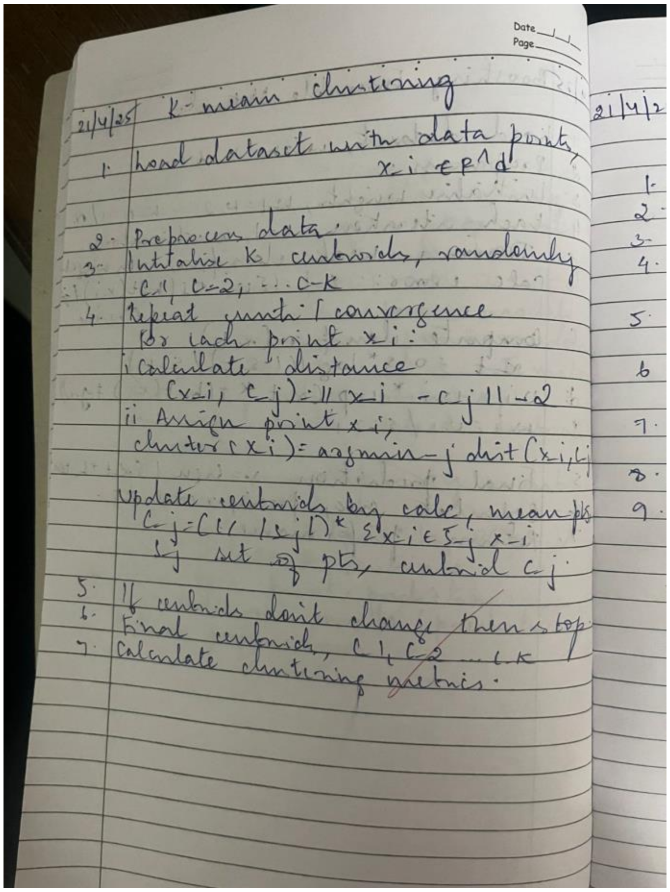
```
X_train_i, X_test_i, y_train_i, y_test_i = train_test_split(X_income, y_income, test_size=0.3,
random_state=42)

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:



21/4/25 K-mean clustering

1. Load dataset with data points, $x_i \in R^d$
2. Preprocess data.
3. Initialize K centroids, randomly $c_1, c_2, \ldots c_k$
4. Repeat until convergence
   for each point x_i:
   i Calculate distance
   $(x_i, c_j) = \|x_i - c_j\|^2$
   ii Assign point x_i,
   cluster(x_i) = argmin_j dist(x_i, c_j)
   Update centroids by calc. mean pts
   $c_j = (1/|S_j|) * \sum_{x_i \in S_j} x_i$
   S_j set of pts, centroid c_j
5. If centroids don't change then stop
6. Final centroids, $c_1, c_2 \ldots c_k$
7. Calculate clustering metrics.

Code:

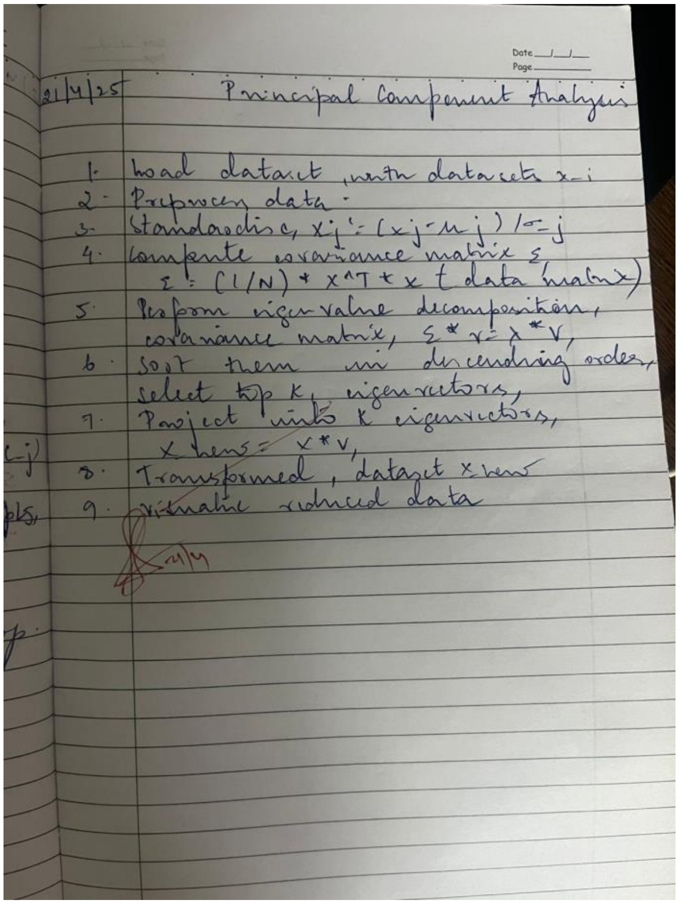
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from scipy import stats
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report, 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:



21/4/25 Principal Component Analysis

1. Load dataset, with datasets x_i
2. Preprocess data:
3. Standardise, $x_j' = (x_j - \mu_j) / \sigma_j$
4. Compute covariance matrix Σ
   $\Sigma = (1/N) * X^T * X$ (data matrix)
5. Perform eigen-value decomposition, covariance matrix, $\Sigma * v = \lambda * v$,
6. Sort them in descending order, select top k eigenvectors,
7. Project onto k eigenvectors, $X_{new} = X * V$,
8. Transformed dataset X_{new}
9. Visualize reduced data

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]}")
```