

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



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Department of Computer Science and Engineering



CERTIFICATE

This is to certify that the Lab work entitled “Machine Learning (23CS6PCMAL)” carried out by **Pratik Jana (1BM22CS356)**, who is bonafide student of **B.M.S. College of Engineering**. It is in partial fulfillment for the award of **Bachelor of Engineering in Computer Science and Engineering** of the Visvesvaraya Technological University, Belgaum. The Lab report has been approved as it satisfies the academic requirements in respect of a Machine Learning (23CS6PCMAL) work prescribed for the said degree.

| | |
|--|---|
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|--|---|

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GITHUB LINK: [pratik03092003/ML-LAB](https://github.com/pratik03092003/ML-LAB)

Program 1

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

Screenshot

```
1. Initializing values directly into Dataframe

import pandas as pd
data = {
    'Name' : ['A', 'B', 'C', 'D']
    'Marks' : [10, 9, 8, 10]
    'USN' : ['351', '352', '353', '356']
}

df = pd.DataFrame(data)
print("Sample data:")
print(df.head(1))

2. Importing dataset from sklearn dataset
from sklearn.datasets import load_diabetes
df = pd.DataFrame(load_diabetes(), columns=load_diabetes().feature_names)

df['target'] = load_diabetes().target
print("Sample data:")
print(df.head(1))

3. Importing dataset from specific .csv file
from sklearn.datasets import load_diabetes
file = pd.read_csv('file-path')
print("Sample data:")
print(df.head(1))
```

Code:

```
import pandas as pd

from sklearn.datasets import load_diabetes


# Part 1: Student data

student_data = {

    'USN': ['1A18CS001', '1A18CS002', '1A18CS003', '1A18CS004', '1A18CS005'],

    'Name': ['Alice', 'Bob', 'Charlie', 'David', 'Eve'],

    'Marks': [85, 78, 92, 88, 75]

}

student_df = pd.DataFrame(student_data)

print("Student Data:")

print(student_df)

print("\n" + "-"*50 + "\n")


# Part 2: Load diabetes dataset from sklearn

diabetes_data = load_diabetes()

diabetes_df = pd.DataFrame(diabetes_data.data, columns=diabetes_data.feature_names)

diabetes_df['target'] = diabetes_data.target

print("Scikit-learn Diabetes Dataset:")

print(diabetes_df.head())

print("\n" + "-"*50 + "\n")


# Part 3: Load sample sales data from CSV
```

try:

```
sales_df = pd.read_csv('sample_sales_data.csv')
```

```
print("Sample Sales Data:")
```

```
print(sales_df.head())
```

except FileNotFoundError:

```
print("sample_sales_data.csv not found.")
```

```
print("\n" + "-"*50 + "\n")
```

Part 4: Load diabetes dataset from external CSV

try:

```
diabetes_csv_df = pd.read_csv('Dataset of Diabetes .csv')
```

```
print("Diabetes Dataset from CSV:")
```

```
print(diabetes_csv_df.head())
```

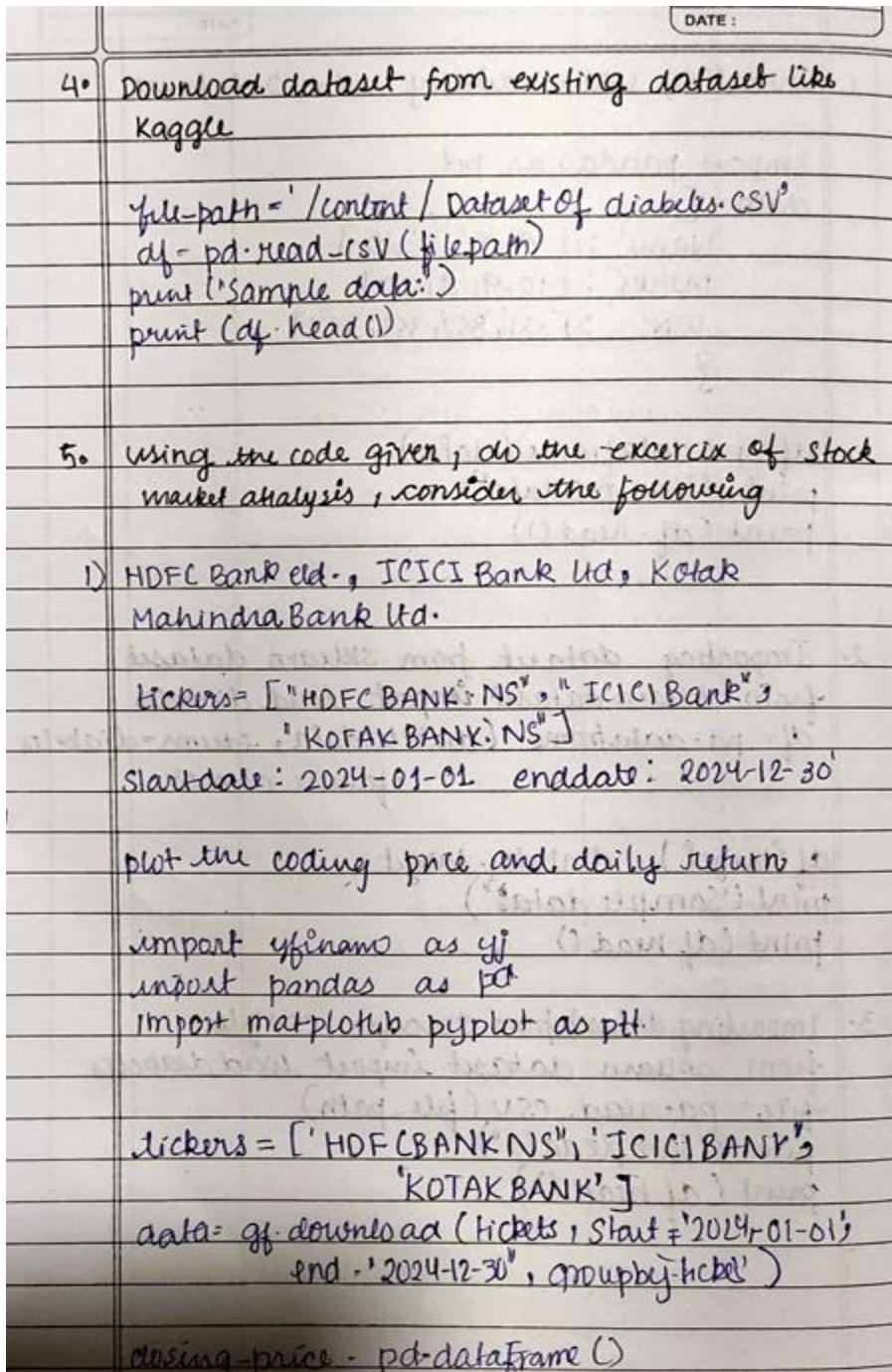
except FileNotFoundError:

```
print("Dataset of Diabetes .csv not found.")
```

Program 2

Demonstrate various data pre-processing techniques for a given dataset

Screenshot:



A screenshot of a handwritten document on lined paper, showing two numbered tasks. Task 4 involves downloading a dataset from Kaggle and reading it into a pandas DataFrame. Task 5 involves using yfinance to download stock data for three banks (HDFC, ICICI, and Kotak) from January 1, 2024, to December 30, 2024, and then plotting the closing price and daily returns. The code is written in Python and includes comments in Hindi.

```
4. Download dataset from existing dataset like Kaggle

file-path = '/content/Dataset of diabetes.csv'
df = pd.read_csv(file-path)
print('Sample data:')
print(df.head(1))

5. Using the code given, do the exercise of stock market analysis, consider the following:

1) HDFC Bank Ltd., ICICI Bank Ltd., Kotak Mahindra Bank Ltd.

tickers = ["HDFCBANK.NS", "ICICIBANK", "KOTAKBANK.NS"]
startdate = '2024-01-01' enddate = '2024-12-30'

plot the closing price and daily return.

import yfinance as yf
import pandas as pd
import matplotlib.pyplot as plt

tickers = ['HDFCBANK.NS', 'ICICIBANK', 'KOTAKBANK']
data = yf.download(tickers, start='2024-01-01', end='2024-12-30', groupby='ticker')

closing-price = pd.DataFrame()
```



```

daily_returns = pd.DataFrame()
for ticker in tickers:
    stock_data = data[tickers]
    closing_price[ticker] = stock_data["close"]
    daily_returns[ticker] = stock_data["close"]
    get_change()

```

Write the python code, consider the filename as "housing.csv"

- (i) to load csv file into the DF
- (ii) display info. of all numerical
- (iii) to display, statistical info of all numerical
- (iv) to display the count of unique labels 'oceanproximity'
- (v) to display which attribute values count greater than zero

```

import pandas as pd
df = pd.read_csv('housing.csv')
print(df.info())
print(df.describe())

```

from sklearn.preprocessing import MinMaxScaler, StandardScaler

```

diabetes_df = pd.read_csv('/content/pattern/
                        Dataset.csv')
adult_income_df = pd.read_csv("adult.csv")

```

```

for column in the_diabetes_df.select_dtypes(
    include = ['Obj']).columns:
    diabetes_df[column], errors =

```


diabetes-df.fillna(diabetes-df.mean(), inplace=True)

def remove_outlier(df, column):

Q1 = df[column].quantile(0.25)

Q3 = df[column].quantile(0.75)

IQR = Q3 - Q1

LB = Q1 - 1.5 * IQR

UB = Q3 + 1.5 * IQR

Code:

```
import yfinance as yf

import pandas as pd

import matplotlib.pyplot as plt

tickers = ["HDFCBANK.NS", "ICICIBANK.NS", "KOTAKBANK.NS"]

# Fetch historical data for the last 1 year

data = yf.download(tickers, start="2024-01-01", end="2024-12-30", group_by='ticker')

hdfc_data = data['HDFCBANK.NS']

hdfc_data['Daily Return'] = hdfc_data['Close'].pct_change()

ic_data = data['ICICIBANK.NS']

ic_data['Daily Return'] = ic_data['Close'].pct_change()

kb_data = data['KOTAKBANK.NS']

kb_data['Daily Return'] = kb_data['Close'].pct_change()

plt.figure(figsize=(12, 6))

plt.subplot(2, 1, 1)

hdfc_data['Close'].plot(title="HDFC Bank - Closing Price")

plt.subplot(2, 1, 2)

hdfc_data['Daily Return'].plot(title="HDFC Bank - Daily Returns", color='orange')
```

```
plt.tight_layout()
```

```
plt.show()
```

```
plt.figure(figsize=(12, 6))
```

```
plt.subplot(2, 1, 1)
```

```
ic_data['Close'].plot(title="ICICI Bank - Closing Price")
```

```
plt.subplot(2, 1, 2)
```

```
ic_data['Daily Return'].plot(title="ICICI Bank - Daily Returns", color='orange')
```

```
plt.tight_layout()
```

```
plt.show()
```

```
plt.figure(figsize=(12, 6))
```

```
plt.subplot(2, 1, 1)
```

```
kb_data['Close'].plot(title="Kotak Bank - Closing Price")
```

```
plt.subplot(2, 1, 2)
```

```
kb_data['Daily Return'].plot(title="Kotak Bank - Daily Returns", color='orange')
```

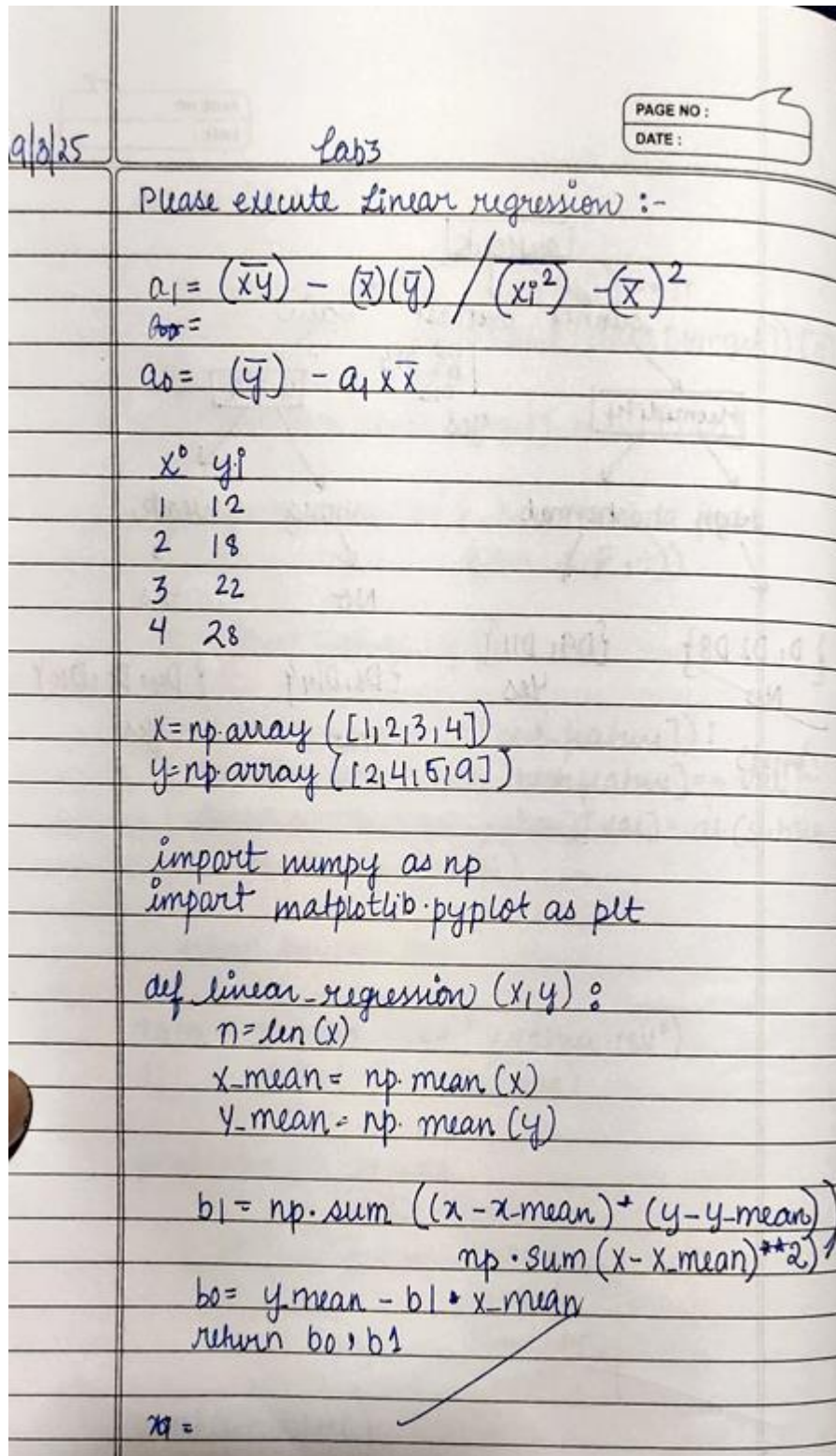
```
plt.tight_layout()
```

```
plt.show()
```

Program 3

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset

Screenshot



```
b0, b1 = linear_regression(x_i, y_i)
print(f"y = {b0:.2f} + {b1:.2f}x")
```

```
plt.scatter(x_i, y_i, color='blue', label='Data points')
plt.plot(x_i, b0 + b1 * x_i, color='red', label='Best-fit line')
plt.xlabel('X (Independent Variable)')
plt.ylabel('Y (Dependent Variable)')
plt.legend()
plt.title('Linear Regression')
plt.show()
```

$$Y = 6.20 + 5.60X$$

Matrix method

```
import numpy as np
import matplotlib.pyplot as plt
def linear_regression_matrix(x, y)
    x = np.column_stack((np.ones(len(x)), x))
    y = np.array(y).reshape(-1, 1)
```

```
    B = np.linalg.inv(x.T @ x) @ x.T @ y
    return B.flatten()
```

```
xi = np.array([1, 2, 3, 4, 5])
yi = np.array([2, 3, 5, 6, 8])
```

```
bo, b1 = linear_regression_matrix(xi, yi)
print(bo, b1)
```

```
plt.scatter(xi, yi, color='blue', label='Data points')
plt.plot(xi, bo + b1 * xi, color='red', label='Best fit line')
```

```
plt.xlabel('x (Independent Variable)')
plt.ylabel('y (Independent Variable)')
plt.legend()
plt.title("Linear Regression (Matrix Method)")
plt.show()
```

$$y = 0.30 + 1.50x$$

Code:

```
import matplotlib.pyplot as plt

x = list(map(float, input("Enter X values separated by space: ").split()))
y = list(map(float, input("Enter Y values separated by space: ").split()))

n = len(x)

sum_x = sum(x)

sum_y = sum(y)

sum_x2 = sum(xi**2 for xi in x)

sum_xy = sum(x[i] * y[i] for i in range(n))

a1 = (n * sum_xy - sum_x * sum_y) / (n * sum_x2 - sum_x**2)

a0 = (sum_y - a1 * sum_x) / n

print("\nLinear Regression Equation:")

print(f'y = {a0:.2f} + {a1:.2f}x')

x_test = float(input("\nEnter a value of x to predict y: "))

y_pred = a0 + a1 * x_test

print(f'Predicted y: {y_pred:.2f}')

plt.scatter(x, y, color='blue', label='Data Points')

x_line = [min(x) - 1, max(x) + 1]

y_line = [a0 + a1 * x_val for x_val in x_line]

plt.plot(x_line, y_line, color='red', label='Regression Line')

plt.scatter(x_test, y_pred, color='green', label=f'Prediction: ({x_test}, {y_pred:.2f})')

plt.xlabel('X values')

plt.ylabel('Y values')
```

```

plt.title('Linear Regression Visualization')

plt.legend()

plt.grid(True)

plt.show()


import numpy as np

import matplotlib.pyplot as plt


x = np.array(list(map(float, input("Enter X values separated by space: ").split()))))
y = np.array(list(map(float, input("Enter Y values separated by space: ").split()))))

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

beta = np.linalg.inv(X.T @ X) @ X.T @ y

print("\nLinear Regression Equation (Matrix Form):")

print(f'y = {beta[0]:.2f} + {beta[1]:.2f}x')

x_test = float(input("\nEnter a value of x to predict y: "))

y_pred = beta[0] + beta[1] * x_test

print(f'Predicted y: {y_pred:.2f}')

plt.scatter(x, y, color='blue', label='Data Points')

x_line = np.linspace(min(x) - 1, max(x) + 1, 100)

y_line = beta[0] + beta[1] * x_line

plt.plot(x_line, y_line, color='red', label='Regression Line')

plt.scatter(x_test, y_pred, color='green', label=f'Prediction: ({x_test}, {y_pred:.2f})')

plt.xlabel('X values')

plt.ylabel('Y values')

```

```
plt.title('Linear Regression (Matrix Form)')
```

```
plt.legend()
```

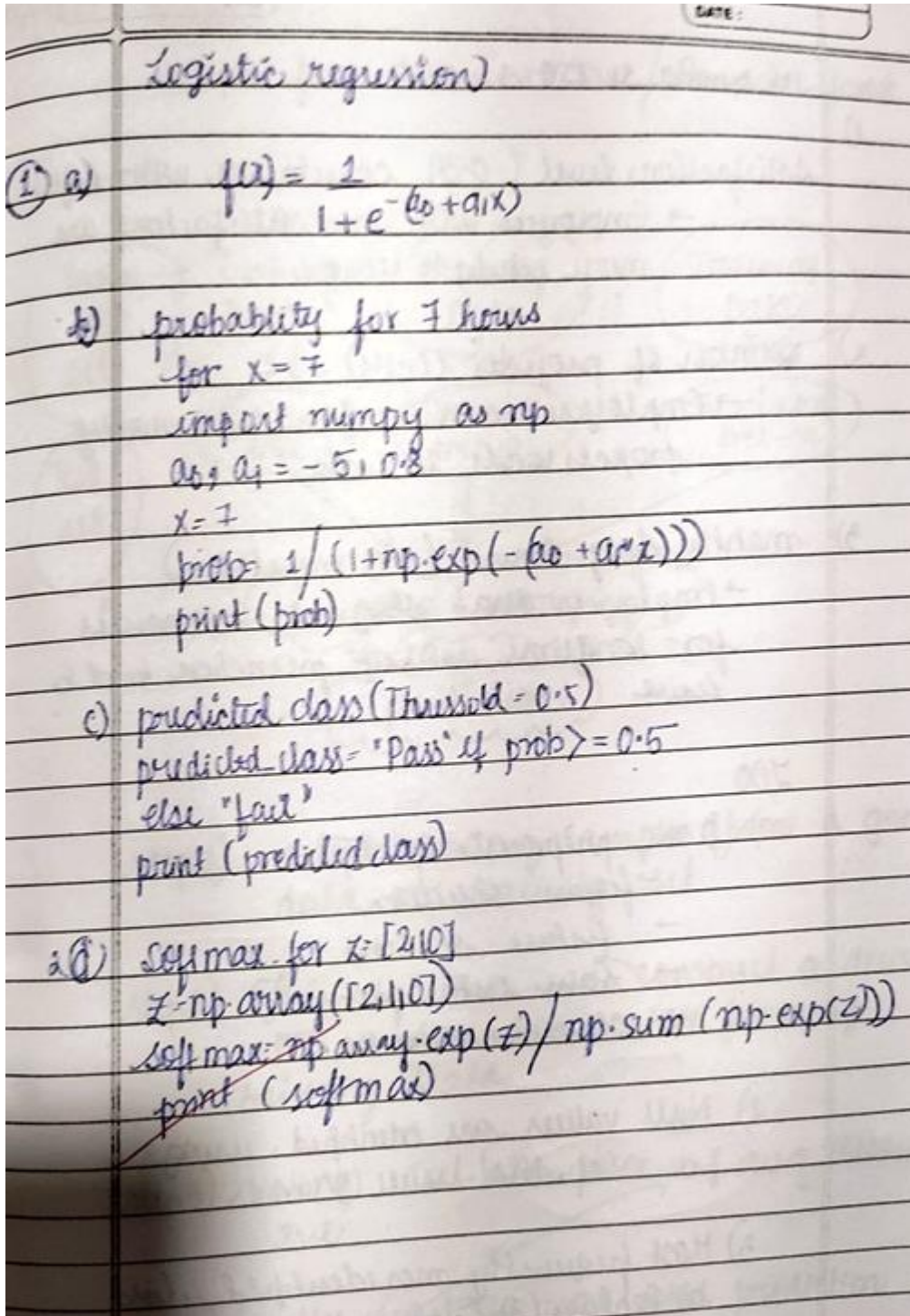
```
plt.grid(True)
```

```
plt.show()
```

Program 4

Build Logistic Regression Model for a given dataset

Screenshot



HR-comm-a-SV-CSV

1)

Satisfaction level (-0.39 correlation with left)

→ Employees with low satisfaction are more likely to leave

2) Number of projects (0.14)

→ Employees with too few or too many projects tends to leave

3) monthly avg hours (0.13 correlated)

→ Employees that stay at companies for long time without promotion tend to leave

200

1) Data preprocessing steps

→ feature selection

→ feature scaling

→ Train test split

→ class encoding

2) Null values are identified using:
`zoo.data.isnull().sum()`

3) Most frequently missing identified class

1) Reptiles (3) & Amphibians (5)

2) Invertebrates (4) & Bugs (6)

3) fish (4) & amphibians (5)

3/1/2020

Code:

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import LabelEncoder

from sklearn.linear_model import LogisticRegression

from sklearn.metrics import accuracy_score, confusion_matrix, classification_report


# Load dataset

df = pd.read_csv("HR_comma_sep.csv")


# Convert categorical variables to numerical

label_enc = LabelEncoder()
```

```
df["salary"] = label_enc.fit_transform(df["salary"])

df["Department"] = label_enc.fit_transform(df["Department"])

# Step 1: Exploratory Data Analysis (EDA)

correlation = df.corr()["left"].sort_values(ascending=False)

print("\nFeature Correlation with Employee Retention:\n", correlation)
```

```
# Step 2: Impact of Salary on Retention

plt.figure(figsize=(6,4))

sns.barplot(x="salary", y="left", data=df, ci=None)

plt.xlabel("Salary Level (Encoded)")

plt.ylabel("Retention Rate")

plt.title("Impact of Salary on Employee Retention")

plt.show()
```

```
# Step 3: Correlation between Department and Retention

plt.figure(figsize=(8,4))

sns.barplot(x="Department", y="left", data=df, ci=None)

plt.xlabel("Department (Encoded)")

plt.ylabel("Retention Rate")

plt.title("Department vs Employee Retention")

plt.show()
```

```
# Step 4: Logistic Regression Model
```

```
features = ["satisfaction_level", "last_evaluation", "number_project", "average_monthly_hours",  
            "time_spend_company", "salary"]
```

```
X = df[features]
```

```
y = df["left"]
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
model = LogisticRegression()
```

```
model.fit(X_train, y_train)
```

```
# Step 5: Model Accuracy
```

```
y_pred = model.predict(X_test)
```

```
accuracy = accuracy_score(y_test, y_pred)
```

```
print(f"\nModel Accuracy: {accuracy:.2f}")
```

```
# Display Confusion Matrix
```

```
conf_matrix = confusion_matrix(y_test, y_pred)
```

```
print("\nConfusion Matrix:\n", conf_matrix)
```

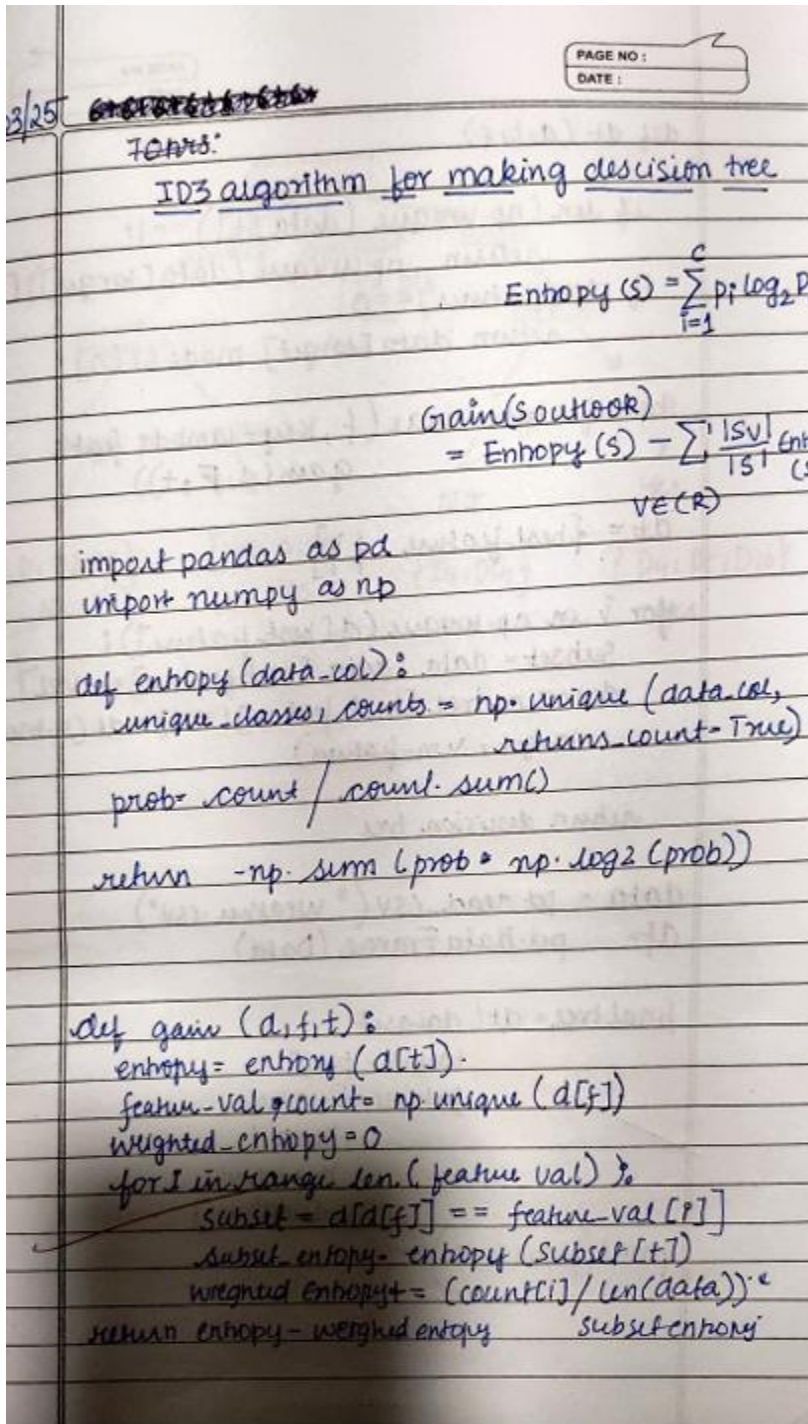
```
# Display Classification Report
```

```
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

Program 5

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

Screenshot



```
def dt (data, f)
```

```
    if len(np.unique(data[f])) == 1:
```

```
        return np.unique(data[target])[0]
```

```
    if len(features) == 0
```

```
        return data[target].mode()[0]
```

```
    best-feature = max(f, key = lambda feat:
                        gain(data, feat))
```

```
    dt = {best-feature: {}}
```

```
    for i in np.unique(data[best-feature]):
```

```
        subset = data[data[best-feature] == i]
```

```
        decision tree[best-feature][i] = dt(subset,
                                             target,
                                             num-features)
```

```
    return decision tree
```

```
data = pd.read_csv("weather.csv")
```

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

```
final tree = dt(data, set
```

```
    target = 'play',
```

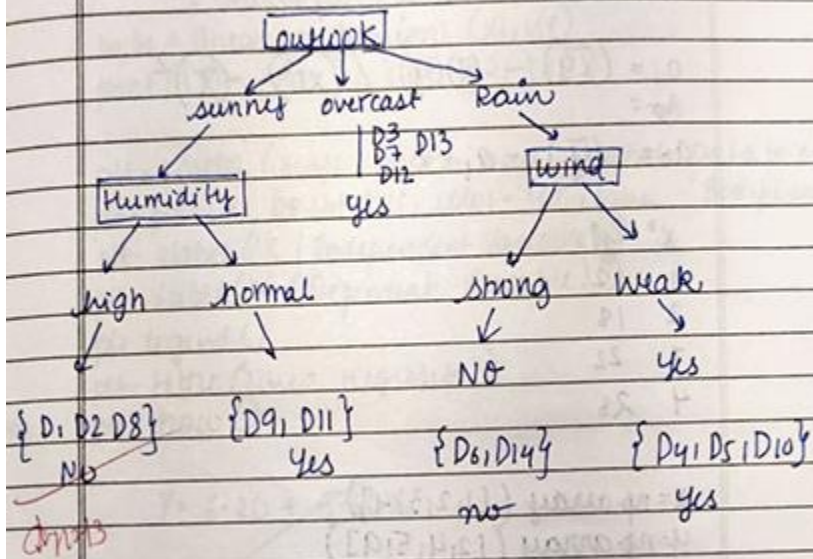
```
    features = ['windspeed',
```

```
                'temp',
```

```
                'humidity',
```

```
                'wind', ]
```

```
print(final tree)
```

Code:

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import LabelEncoder

from sklearn.linear_model import LogisticRegression

from sklearn.metrics import accuracy_score, confusion_matrix, classification_report


# Load dataset

df = pd.read_csv("HR_comma_sep.csv")


# Convert categorical variables to numerical

label_enc = LabelEncoder()

df["salary"] = label_enc.fit_transform(df["salary"])

df["Department"] = label_enc.fit_transform(df["Department"])


# Step 1: Exploratory Data Analysis (EDA)

correlation = df.corr()["left"].sort_values(ascending=False)

print("\nFeature Correlation with Employee Retention:\n", correlation)


# Step 2: Impact of Salary on Retention

plt.figure(figsize=(6,4))
```

```
sns.barplot(x="salary", y="left", data=df, ci=None)

plt.xlabel("Salary Level (Encoded)")

plt.ylabel("Retention Rate")

plt.title("Impact of Salary on Employee Retention")

plt.show()
```

Step 3: Correlation between Department and Retention

```
plt.figure(figsize=(8,4))

sns.barplot(x="Department", y="left", data=df, ci=None)

plt.xlabel("Department (Encoded)")

plt.ylabel("Retention Rate")

plt.title("Department vs Employee Retention")

plt.show()
```

Step 4: Logistic Regression Model

```
features = ["satisfaction_level", "last_evaluation", "number_project", "average_monthly_hours",
"time_spend_company", "salary"]
```

```
X = df[features]
```

```
y = df["left"]
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
model = LogisticRegression()
```

```
model.fit(X_train, y_train)
```

```
# Step 5: Model Accuracy
```

```
y_pred = model.predict(X_test)
```

```
accuracy = accuracy_score(y_test, y_pred)
```

```
print(f'\nModel Accuracy: {accuracy:.2f}')
```

```
# Display Confusion Matrix
```

```
conf_matrix = confusion_matrix(y_test, y_pred)
```

```
print("\nConfusion Matrix:\n", conf_matrix)
```

```
# Display Classification Report
```

```
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

Program 6

Build KNN Classification model for a given dataset

Screenshot

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| Sapna | | KNN | | |
|--------|----------------|----------------|--|----|
| Dist | (1,1) | (3,7) | | |
| 1,1 | 0.0 | $\sqrt{52}$ | | C1 |
| 1.5, 2 | $\sqrt{11.25}$ | $\sqrt{27.25}$ | | C1 |
| 3, 4 | $\sqrt{13}$ | $\sqrt{13}$ | | C2 |
| 5, 7 | $\sqrt{52}$ | $\sqrt{8}$ | | C2 |
| 35, 5 | $\sqrt{27.25}$ | $\sqrt{6.25}$ | | C2 |
| 45, 5 | $\sqrt{27.25}$ | $\sqrt{4.15}$ | | C2 |
| 35, 45 | $\sqrt{18.5}$ | $\sqrt{8.5}$ | | C2 |

$\bar{x} = \frac{1+3}{2}, \frac{1+7}{2} = (1.25, 1.5)$
 $\therefore C2 = (3.9, 5.1)$

| | (1.25, 1.5) | (3.9, 5.1) | cluster |
|----------|-------------|------------|---------|
| (1,1) | 0.56 | 9.25 | C1 |
| (1.5, 2) | 0.56 | 4.04 | C2 |
| (3, 4) | 2.50 | 1.42 | C2 |
| (5, 7) | 6.10 | 2.16 | C2 |
| (35, 5) | 2.85 | 0.41 | C2 |
| (45, 5) | 3.32 | 0.61 | C2 |
| (35, 45) | 2.63 | 0.51 | C2 |

cluster (1,1) (1.5, 2)
 (3, 4), (35, 5), (35, 45)
 (5, 7), (45, 5)

Code:

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

file_path = input("Enter the path to your CSV file: ")
df = pd.read_csv(file_path)

# Automatically select the target column (assuming it's the last column)
target_column = df.columns[-1]

# Splitting features (X) and target variable (y)
X = df.iloc[:, :-1] # All columns except last (features)
y = df.iloc[:, -1] # Last column (target)

# Encode categorical target variable if necessary
if y.dtype == 'object':
    label_encoder = LabelEncoder()
    y = label_encoder.fit_transform(y)

# Convert categorical features to numerical if any
X = pd.get_dummies(X, drop_first=True)

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

# Standardize the data
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Determine optimal k (square root heuristic)
k = int(np.sqrt(len(y_train)))
if k % 2 == 0:
    k += 1

# Train the KNN classifier
knn = KNeighborsClassifier(n_neighbors=k)
knn.fit(X_train, y_train)

# Make predictions
y_pred = knn.predict(X_test)
```



```
# Display accuracy score
accuracy = accuracy_score(y_test, y_pred)
print(f"\nAccuracy Score: {accuracy:.2f}")

# Display confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("\nConfusion Matrix:\n", conf_matrix)

# Display classification report
class_report = classification_report(y_test, y_pred)
print("\nClassification Report:\n", class_report)

# Plot Confusion Matrix
plt.figure(figsize=(6,5))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues", xticklabels=np.unique(y),
yticklabels=np.unique(y))
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.title("Confusion Matrix")
plt.show()
```

Program 7

Implement Random Forest ensemble method on a given dataset

Lab 7 : Implement Random forest

PAGE NO :
DATE : 7/5

Observation

Default accuracy (n_estimator=10) : 1.0000
Best accuracy : 1.000 with n_estimator=1
Confusion Matrix :

$$\begin{bmatrix} [19 & 0 & 0] \\ [0 & 13 & 0] \\ [0 & 0 & 13] \end{bmatrix}$$

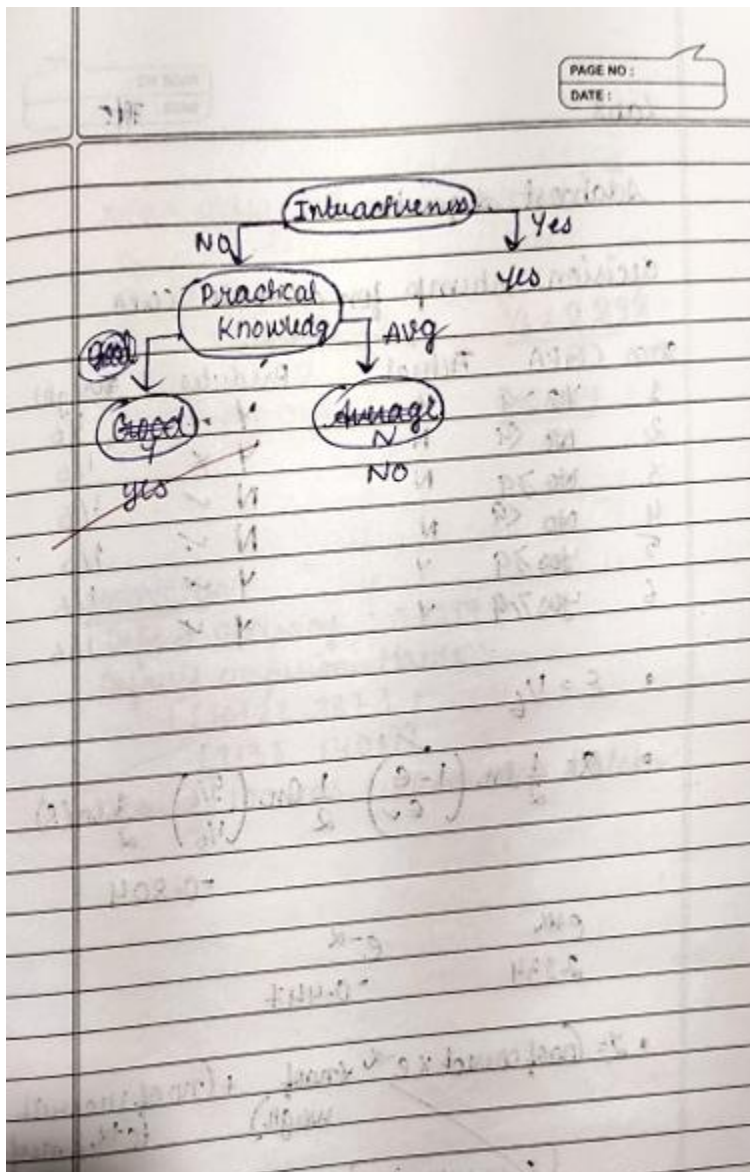
commet

| Sno | CGPA | Interactiveness | Practical Knowledge | Job |
|-----|----------|-----------------|---------------------|----------|
| 1 | ≥ 9 | Y | G | Good |
| 2 | < 9 | N | M | Moderate |
| 3 | > 9 | N | M | Moderate |
| 4 | > 9 | N | M | Moderate |
| 5 | ≥ 9 | Y | M | Moderate |

Decision Tree:

```
graph TD
    CGPA((CGPA)) -- ">= 9" --> Interactiveness((Interactiveness))
    CGPA -- "< 9" --> Y((Y))
    Interactiveness -- "Y" --> Yes((Yes))
    Interactiveness -- "N" --> NO((NO))
```

Screenshot



Code:

```
import pandas as pd

from sklearn.ensemble import RandomForestClassifier

from sklearn.model_selection import train_test_split

from sklearn.metrics import accuracy_score

import matplotlib.pyplot as plt


# Load dataset

df = pd.read_csv("iris.csv")


# Features and target

X = df.drop(columns=["species"])

y = df["species"]


# Split into train/test

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


# 1. Train with default n_estimators = 10

rf_default = RandomForestClassifier(n_estimators=10, random_state=42)

rf_default.fit(X_train, y_train)

y_pred_default = rf_default.predict(X_test)

default_score = accuracy_score(y_test, y_pred_default)


print(f"Accuracy with default (10 trees): {default_score:.4f}")
```

```

# 2. Fine-tune n_estimators

scores = []

tree_range = range(1, 51)

for n in tree_range:

    model = RandomForestClassifier(n_estimators=n, random_state=42)

    model.fit(X_train, y_train)

    y_pred = model.predict(X_test)

    acc = accuracy_score(y_test, y_pred)

    scores.append(acc)

# Plotting results

plt.figure(figsize=(10,5))

plt.plot(tree_range, scores, marker='o')

plt.title("Random Forest Accuracy vs Number of Trees")

plt.xlabel("Number of Trees (n_estimators)")

plt.ylabel("Accuracy")

plt.grid(True)

plt.show()

# Best result

best_score = max(scores)

best_n = tree_range[scores.index(best_score)]

print(f'Best Accuracy = {best_score:.4f} with n_estimators = {best_n}')

```

Program 8

Implement Boosting ensemble method on a given dataset

Screenshot

Lab 8

PAGE NO:
 DATE: 7/11

Adaboost algorithm

decision: stump for attribute CGPA

| Slno | CGPA | Actual | Predicted | Weight |
|------|----------|--------|-----------|--------|
| 1 | ≥ 9 | Y | Y | $1/6$ |
| 2 | < 9 | N | Y | $1/6$ |
| 3 | ≥ 9 | N | N | $1/6$ |
| 4 | < 9 | N | N | $1/6$ |
| 5 | ≥ 9 | Y | Y | $1/6$ |
| 6 | ≥ 9 | Y | Y | $1/6$ |

• $\epsilon = 1/6$

• $\alpha = \frac{1}{2} \ln \left(\frac{1-\epsilon}{\epsilon} \right) = \frac{1}{2} \ln \left(\frac{5/6}{1/6} \right) = \frac{1}{2} \ln(5)$
 $= 0.804$

$e^{+\alpha}$ $e^{-\alpha}$
 2.234 0.447

• $Z = (\text{no of correct} \times e^{-\alpha} \times \text{no of weight}) + (\text{no of incorrect} \times e^{+\alpha} \times \text{no of weight})$

$(5 \times 0.447 \times 1/6) + (1 \times 2.234 \times 1/6)$
 $0.3725 + 0.3723$
 $= 0.744$

of

 $z(5, 2)$

Correct

$$10 = \frac{1}{6} \times 0.447$$

2

-610 013

News of

11. Invoer

$$\frac{1}{6} \times 2.294$$

2

0.5004

Observation)

Default accuracy = 0.8277

Default confusion Matrix:

[[10722 387]]

[2138 1406]

moving 100 trees (10 in each batch)

Code:

```
import pandas as pd

import numpy as np

from sklearn.ensemble import AdaBoostClassifier

from sklearn.tree import DecisionTreeClassifier

from sklearn.model_selection import train_test_split

from sklearn.metrics import accuracy_score, classification_report

import matplotlib.pyplot as plt


# Load the dataset

data = pd.read_csv('income.csv')


# Explore the dataset

print(data.head())

print("\nDataset info:")

print(data.info())

print("\nClass distribution:")

print(data['income_level'].value_counts())


# Split into features and target

X = data.drop('income_level', axis=1)

y = data['income_level']


# Encode categorical features (one-hot encoding)
```

```

X = pd.get_dummies(X)

# Check for missing values
if X.isnull().sum().sum() > 0:
    print("Missing values found. Filling missing values with column mean.")
    X = X.fillna(X.mean())

# Split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=42, stratify=y)

# Define base estimator
base_estimator = DecisionTreeClassifier(max_depth=1) # Stump tree for AdaBoost

# Initial AdaBoost model with 10 estimators
ada_model = AdaBoostClassifier(
    estimator=base_estimator,
    n_estimators=10,
    random_state=42
)

# Train the model
ada_model.fit(X_train, y_train)

```

```

# Make predictions

y_pred = ada_model.predict(X_test)


# Evaluate initial model

print("\nInitial Model with 10 estimators:")

print("Accuracy:", accuracy_score(y_test, y_pred))

print("\nClassification Report:")

print(classification_report(y_test, y_pred))


# Fine-tune the number of trees

n_estimators_range = [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 150, 200]

train_scores = []

test_scores = []


for n in n_estimators_range:

    model = AdaBoostClassifier(

        estimator=base_estimator,

        n_estimators=n,

        random_state=42

    )

    model.fit(X_train, y_train)


# Training accuracy

train_pred = model.predict(X_train)

```

```

train_acc = accuracy_score(y_train, train_pred)

train_scores.append(train_acc)


# Test accuracy

test_pred = model.predict(X_test)

test_acc = accuracy_score(y_test, test_pred)

test_scores.append(test_acc)


print(f'n_estimators: {n}, Train Accuracy: {train_acc:.4f}, Test Accuracy: {test_acc:.4f}')


# Find the best number of estimators

best_n = n_estimators_range[np.argmax(test_scores)]

best_score = max(test_scores)


print(f"\nBest performance: n_estimators={best_n} with test accuracy of {best_score:.4f}")


# Plot the results

plt.figure(figsize=(10, 6))

plt.plot(n_estimators_range, train_scores, label='Train Accuracy', marker='o')

plt.plot(n_estimators_range, test_scores, label='Test Accuracy', marker='o')

plt.xlabel('Number of Estimators')

plt.ylabel('Accuracy')

plt.title('AdaBoost Performance vs Number of Estimators')

plt.axvline(x=best_n, color='r', linestyle='--', label=f'Best n_estimators={best_n}')

```

```

plt.legend()

plt.grid()

plt.show()

# Train final model with best number of estimators

final_model = AdaBoostClassifier(

    estimator=base_estimator,

    n_estimators=best_n,

    random_state=42

)

final_model.fit(X_train, y_train)

# Evaluate final model

final_pred = final_model.predict(X_test)

print("\nFinal Model Performance:")

print("Accuracy:", accuracy_score(y_test, final_pred))

print("\nClassification Report:")

print(classification_report(y_test, final_pred))

print("\nFeature Importances:")

feature_importances = pd.Series(final_model.feature_importances_, index=X.columns)

print(feature_importances.sort_values(ascending=False))

```

Program 9

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

Screenshot

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| | <u>Dist</u> | <u>(1,1)</u> | <u>(5,7)</u> | |
|----------|----------------|----------------|--------------|--|
| 1,1 | 0.0 | $\sqrt{5.2}$ | C1 | |
| 1.5, 2 | $\sqrt{1.25}$ | $\sqrt{2.725}$ | C1 | |
| 3, 4 | $\sqrt{13}$ | $\sqrt{13}$ | C2 | |
| 5, 7 | $\sqrt{6.5}$ | $\sqrt{6.5}$ | C2 | |
| 3.5, 5 | $\sqrt{2.725}$ | $\sqrt{6.25}$ | C2 | |
| 4.5, 5 | $\sqrt{2.725}$ | $\sqrt{4.25}$ | C2 | |
| 3.5, 4.5 | $\sqrt{16.5}$ | $\sqrt{8.5}$ | C2 | |

$\mu_1 = \frac{1+1.5}{2}, \frac{1+2}{2} = (1.25, 1.5)$
 $\therefore C_2 = (3.9, 5.1)$

| | <u>(1.5, 1.5)</u> | <u>(3.9, 5.1)</u> | <u>cluster</u> |
|------------|-------------------|-------------------|----------------|
| (1,1) | 0.56 | 3.25 | C1 |
| (1.5, 2) | 0.56 | 4.04 | C2 |
| (3, 4) | 2.80 | 1.42 | C2 |
| (5, 7) | 6.10 | 2.16 | C2 |
| (3.5, 5) | 2.85 | 0.41 | C2 |
| (4.5, 5) | 3.32 | 0.61 | C2 |
| (3.5, 4.5) | 2.63 | 0.51 | C2 |

cluster (1,1) (1.5, 2)
(3, 4), (3.5, 5), (3.5, 4.5)
(4.5, 5)

$$Z = [-4.30535, 3.73635, 5.69305, -5.12405]$$

Model accuracy

| | Before | After |
|------------------|--------|--------|
| logistic | 0.8833 | 0.8667 |
| SVM | 0.8728 | 0.8556 |
| Random forest | 0.8889 | 0.8722 |

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Code:

```
import pandas as pd

import matplotlib.pyplot as plt

from sklearn.preprocessing import StandardScaler

from sklearn.cluster import KMeans


# Load your iris dataset

df = pd.read_csv("iris.csv")


# Use only Petal Length and Petal Width

X = df[["petal_length", "petal_width"]]


# Scale the features

scaler = StandardScaler()

X_scaled = scaler.fit_transform(X)


# Elbow Method to determine optimal k

inertia = []

k_range = range(1, 11)

for k in k_range:

    kmeans = KMeans(n_clusters=k, random_state=42)

    kmeans.fit(X_scaled)

    inertia.append(kmeans.inertia_)


# Plot Elbow Curve
```

```

plt.figure(figsize=(8, 5))

plt.plot(k_range, inertia, marker='o')

plt.title("Elbow Method for Optimal k")

plt.xlabel("Number of Clusters (k)")

plt.ylabel("Inertia")

plt.grid(True)

plt.show()


# Final KMeans with optimal k (e.g., 3 from elbow)

optimal_k = 3

kmeans = KMeans(n_clusters=optimal_k, random_state=42)

df['Cluster'] = kmeans.fit_predict(X_scaled)


# Visualize Clusters

plt.figure(figsize=(8, 5))

plt.scatter(X_scaled[:, 0], X_scaled[:, 1], c=df['Cluster'], cmap='viridis', s=50)

plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1],

            color='red', marker='X', label='Centroids')

plt.xlabel("Petal Length (scaled)")

plt.ylabel("Petal Width (scaled)")

plt.title(f"K-Means Clustering (k={optimal_k}) on Iris Petal Features")

plt.legend()

plt.grid(True)

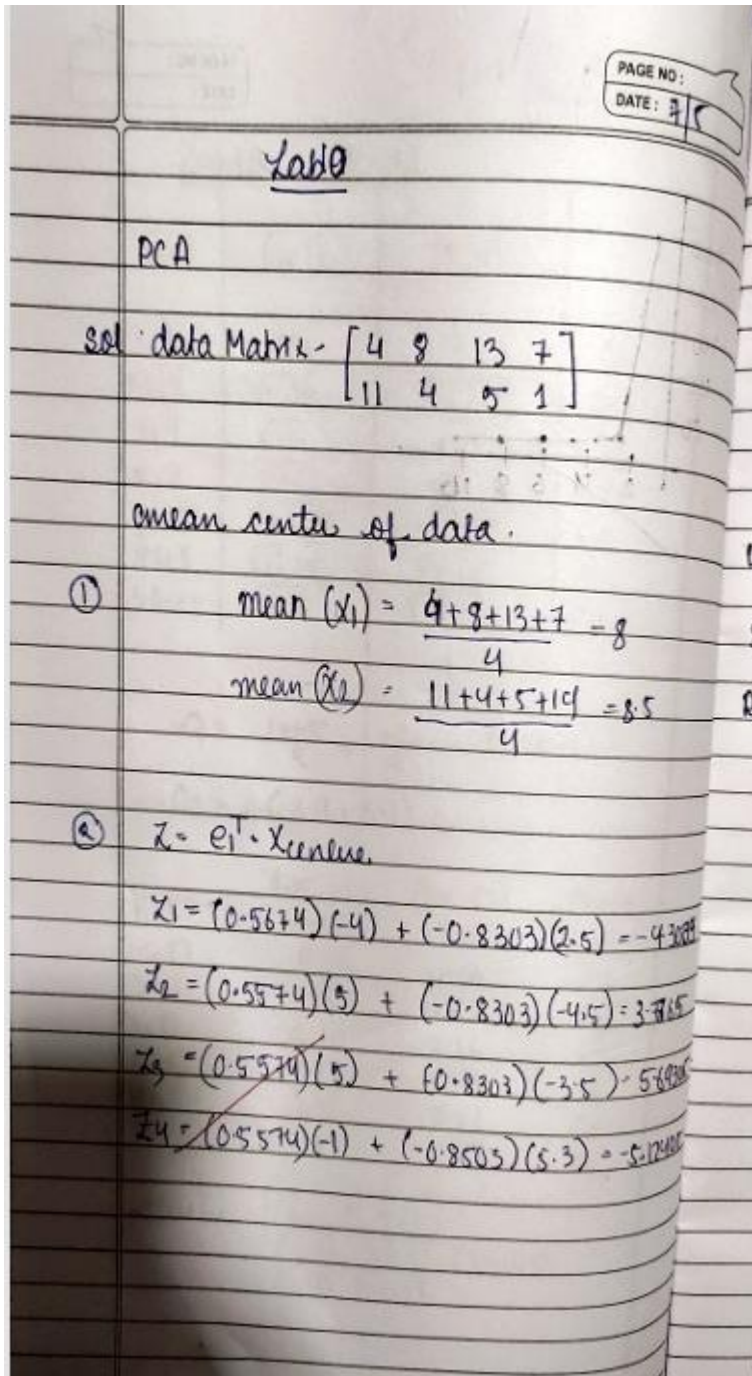
plt.show()

```

Program 10

Implement Dimensionality reduction using Principal Component Analysis (PCA) method

Screenshot



$$Z = [-4.30535, 3.73635, 5.69305, -5.12405]$$

Model accuracy

| | Before | After |
|------------------|--------|--------|
| logistic | 0.8833 | 0.8667 |
| SVM | 0.8728 | 0.8556 |
| Random forest | 0.8889 | 0.8722 |

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Code:

```
import pandas as pd

from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler

from sklearn.compose import ColumnTransformer

from sklearn.model_selection import train_test_split

from sklearn.svm import SVC

from sklearn.linear_model import LogisticRegression

from sklearn.ensemble import RandomForestClassifier

from sklearn.decomposition import PCA

from sklearn.metrics import accuracy_score

from sklearn.pipeline import Pipeline


# Load dataset

data = pd.read_csv('heart.csv')


# Separate features and target

X = data.drop('HeartDisease', axis=1)

y = data['HeartDisease']


# Identify categorical and numerical columns

cat_cols = ['Sex', 'ChestPainType', 'RestingECG', 'ExerciseAngina', 'ST_Slope']

num_cols = [col for col in X.columns if col not in cat_cols]


# Label encode binary categorical columns with two categories (e.g. Sex, ExerciseAngina)
```

```

label_enc_cols = ['Sex', 'ExerciseAngina']

le = LabelEncoder()

for col in label_enc_cols:

    X[col] = le.fit_transform(X[col])


# For other categorical columns with more than two categories, apply OneHotEncoding
onehot_cols = list(set(cat_cols) - set(label_enc_cols))


# Preprocessing pipeline: OneHotEncoding + scaling numerical features
preprocessor = ColumnTransformer(

    transformers=[

        ('onehot', OneHotEncoder(drop='first'), onehot_cols),

        ('scaler', StandardScaler(), num_cols)

    ],

    remainder='passthrough' # To keep label encoded columns as is

)


# Split data into train/test sets

X_train, X_test, y_train, y_test = train_test_split(

    X, y, test_size=0.3, random_state=42, stratify=y)


# Helper function to train and evaluate a model

def train_evaluate_model(model, X_train, X_test, y_train, y_test):

    pipeline = Pipeline(steps=[('preprocessor', preprocessor),

```

```

        ('classifier', model)])

    pipeline.fit(X_train, y_train)

    y_pred = pipeline.predict(X_test)

    acc = accuracy_score(y_test, y_pred)

    return acc, pipeline


# Train and evaluate SVM

svm = SVC(random_state=42)

svm_acc, svm_pipeline = train_evaluate_model(svm, X_train, X_test, y_train, y_test)


# Train and evaluate Logistic Regression

logreg = LogisticRegression(max_iter=1000, random_state=42)

logreg_acc, logreg_pipeline = train_evaluate_model(logreg, X_train, X_test, y_train, y_test)


# Train and evaluate Random Forest

rf = RandomForestClassifier(random_state=42)

rf_acc, rf_pipeline = train_evaluate_model(rf, X_train, X_test, y_train, y_test)


print(f"Accuracy Scores without PCA:\nSVM: {svm_acc:.4f}\nLogistic Regression: {logreg_acc:.4f}\nRandom Forest: {rf_acc:.4f}")


# Now apply PCA for dimensionality reduction after preprocessing (scaling + encoding)

# We modify the pipeline to include PCA before classification


def train_evaluate_model_pca(model, X_train, X_test, y_train, y_test, n_components):

```



```

pca = PCA(n_components=n_components, random_state=42)

pipeline = Pipeline(steps=[

    ('preprocessor', preprocessor),

    ('pca', pca),

    ('classifier', model)

])

pipeline.fit(X_train, y_train)

y_pred = pipeline.predict(X_test)

acc = accuracy_score(y_test, y_pred)

return acc, pipeline


# Choose number of components to keep 95% variance or fixed number (e.g. 5)

# Here let's pick 5 components arbitrarily

n_components = 5


svm_pca_acc, _ = train_evaluate_model_pca(svm, X_train, X_test, y_train, y_test, n_components)

logreg_pca_acc, _ = train_evaluate_model_pca(logreg, X_train, X_test, y_train, y_test,
n_components)

rf_pca_acc, _ = train_evaluate_model_pca(rf, X_train, X_test, y_train, y_test, n_components)


print(f"\nAccuracy Scores with PCA (n_components={n_components}):")

print(f"SVM: {svm_pca_acc:.4f}")

print(f"Logistic Regression: {logreg_pca_acc:.4f}")

print(f"Random Forest: {rf_pca_acc:.4f}")

```