Mini Project Report : Defaulter Prediction

BATCH: B1

Student Names:

Prajakta Jadhav-UCE2022516 Sanjana Inapakolla-UCE2022510 Ishani Deshmukh-UCE2022512

Synopsis:

1)Title: Attendance-Based Defaulter Prediction System

2)Problem Statement:

Our project aims to develop an efficient system for predicting student defaulters based on their attendance records. By analyzing attendance patterns, we seek to forecast whether a student is likely to default on academic obligations.

3) Introduction:

Our project focuses on developing a predictive system to identify student defaulters based on their attendance records using supervised learning techniques, specifically employing the Random Forest classification model. The dataset provided is in CSV format, containing labels denoted as YES or NO, indicating whether a student is likely to default.

The core aim of our project is to provide educators with a tool that can predict student defaulters for any given month by analyzing their attendance data. By inputting the attendance for the upcoming month, our system generates predictions for all students, aiding teachers in proactive intervention and support.

Key Features:

- **1)Random Forest Model:** Our system employs a Random Forest classification model to predict student defaulters. Random Forest is a powerful algorithm that works by creating multiple decision trees and combining their predictions. It's known for its ability to handle complex datasets effectively and produce accurate results.
- **2)Real-time Prediction:** Educators can input the attendance data for the next month, and our system generates predictions for all students promptly, enabling timely intervention.
- **3)Data Integrity Check:** Our system includes functionality to identify missing values in the CSV file, ensuring data accuracy and completeness. Which helps teacher to modify CSV file easily.
- **4)Outlier Detection:** Using outlier detection techniques, our system flags instances where incorrect attendance entries have been made by teachers, such as attendance exceeding the total number of lectures.
- **5)Visualization:** Our system offers visualizations depicting student defaulter rates, allowing educators to gain insights into attendance patterns and potential risk factors.
- **6)Model Comparison:** Additionally, our project analyzes the performance of different classification models, including K-Nearest Neighbors (KNN) and Logistic Regression, evaluating their accuracy and potential for overfitting. Among these models, Random Forest emerges as the most effective choice for predicting student defaulters.

By combining machine learning with data visualization and model analysis, our project aims to provide educators with a comprehensive tool for proactive student support, ultimately enhancing academic success and retention rates.

3)Data set information (link,few data samples etc)

The dataset contains the following attributes:

CNumber: Unique identification number assigned to each student.

Name of the Student: Name of the student.

Attendance for each subject: IoT, SE, HS-OB, OE1-SC, OEI-ICCF, IOTL.

Defaulter Status for Each Subject: Indicates whether the student is a defaulter

for each subject.

Overall Defaulter Status: Indicates whether the student is an overall defaulter, based on being a defaulter in at least 3 subjects.

Google Collab **Datasets**

4) Code and output:

Mount Google drive

```
from google.colab import drive
drive.mount('/content/drive')
o/p:
Mounted at /content/drive
Import the necessary libraries
import pandas as pd
from sklearn.model selection import train test split
from sklearn.preprocessing import LabelEncoder
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification report
from scipy import stats
import matplotlib.pyplot as plt
```

K-NN algorithm It giving wrong output

```
# Load the dataset
df = pd.read csv("/content/drive/MyDrive/ML datasets/DefaulterList -
Sheet1 (1).csv")
# Encode the target variable
le = LabelEncoder()
df['Defaulter'] = le.fit transform(df['Defaulter'])
print("Columns in the DataFrame:")
print(df.columns)
# Selecting only the specified columns for features
selected columns = ['IoT', 'SE', 'HS-OB', 'OE1- SC', 'OEI-ICCF', 'IOTL']
X = df[selected columns]
# Target variable
y = df['Defaulter']
0/P:
```

```
Columns in the DataFrame:
Index(['CNumber', 'Name of the Student', 'IoT', 'SE', 'HS-OB', 'OE1- SC',
       'OEI-ICCF', 'IOTL', 'Defaulter(IoT)', 'Defaulter(SE)',
```

```
'Defaulter(HS-OB)', 'Defaulter(OE1- SC)', 'Defaulter(OEI-ICCF)',
       'Defaulter(IOTL)', 'Defaulter'],
      dtype='object')
Training and Testing
# Splitting the dataset into the Training set and Test set
X train, X test, y train, y test = train test split(X, y, test size=0.3,
random state=42)
print("Missing values in X test:", X test.isnull().sum())
0/P:
Missing values in X test: IoT
HS-OB
OE1- SC
           0
OEI-ICCF
IOTL
dtype: int64
Remove the outliers
outlier_indices = []
for column in selected columns:
    outlier index = df[df[column] > 30].index
    outlier indices.extend(outlier index)
    if len(outlier index) > 0:
        print("Outliers for", column, ":")
        for idx in outlier index:
            print("CNumber:", df.at[idx, 'CNumber'], ", Name:", df.at[idx,
'Name of the Student'], ", Subject:", column, ", Value:", df.at[idx,
column])
# Remove outliers from the dataset
df.drop(outlier indices, inplace=True)
0/P:
Outliers for IoT :
CNumber: C22018221430 , Name: AGARWAL MUSKAN , Subject: IoT , Value: 100
```

Implementing Random Forest

100

```
from sklearn.ensemble import RandomForestClassifier
# Initialize the Random Forest classifier
```

CNumber: C22018221431 , Name: JOSHI ADITI ANANT , Subject: IoT , Value:

```
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)

# Train the classifier
rf_classifier.fit(X_train, y_train)

# Predictions on the test set
y_pred = rf_classifier.predict(X_test)

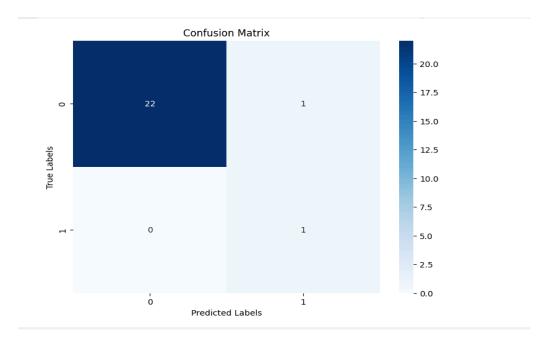
# Evaluate the classifier
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

0/P:

Classification Report:

	precision	recall	f1-score	support
	0 1.00	0.96	0.98	23
	1 0.50	1.00	0.67	1
accurac	У		0.96	24
macro av	g 0.75	0.98	0.82	24
weighted av	g 0.98	0.96	0.96	24

Confusion Matrix



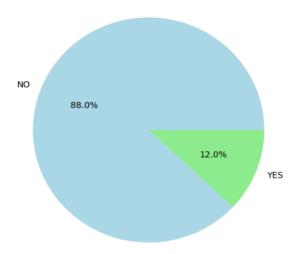
```
# Map the label values to 'YES' and 'NO'
df['Defaulter'] = df['Defaulter'].map({1: 'YES', 0: 'NO'})

# Count the occurrences of each label in the target variable
label_counts = df['Defaulter'].value_counts()

# Plotting the pie chart
plt.figure(figsize=(8, 6))
plt.pie(label_counts, labels=label_counts.index, autopct='%1.1f%%',
colors=['lightblue', 'lightgreen'])
plt.title('Defaulter Classes Distribution')
plt.show()
```

0/P

Defaulter Classes Distribution



Side-by-side chart

```
import matplotlib.pyplot as plt
# Count the occurrences of "YES" and "NO" for each subject column
defaulter counts = {}
subjects = ['IoT', 'SE', 'HS-OB', 'OE1- SC', 'OEI-ICCF', 'IOTL']
for subject in subjects:
    counts = df['Defaulter(' + subject + ')'].value_counts()
    defaulter counts[subject] = counts
# Extract counts for YES and NO
yes_counts = [defaulter_counts[subject].get('YES', 0) for subject in
subjects]
no_counts = [defaulter_counts[subject].get('NO', 0) for subject in
subjects]
# Plotting
fig, ax = plt.subplots(figsize=(10, 6))
# Bar width
bar width = 0.35
# Bar positions
bar positions = range(len(subjects))
```

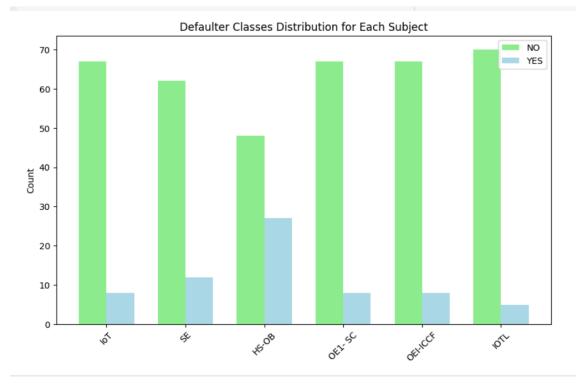
```
# Plotting "NO" counts
ax.bar([pos - bar_width/2 for pos in bar_positions], no_counts, bar_width,
label='NO', color='lightgreen')

# Plotting "YES" counts
ax.bar([pos + bar_width/2 for pos in bar_positions], yes_counts,
bar_width, label='YES', color='lightblue')

# Adding labels and title
ax.set_ylabel('Count')
ax.set_title('Defaulter Classes Distribution for Each Subject')
ax.set_xticks(bar_positions)
ax.set_xticklabels(subjects)
ax.legend()

plt.xticks(rotation=45)
plt.show()
```

0/P:



Testing

```
#USER INPUT TESTING
student_attendance = {
```

```
'IoT': 1,
    'SE': 1,
    'HS-OB':10,
    'OE1- SC': 12,
    'OEI-ICCF': 0,
    'IOTL': 0
}

# Convert the student's attendance into DataFrame
student_df = pd.DataFrame([student_attendance])

# Predict whether the student is a defaulter or not using Random Forest classifier
defaulter_prediction = rf_classifier.predict(student_df)
defaulter_prediction_label = le.inverse_transform(defaulter_prediction)
print("Predicted Defaulter Label:", defaulter_prediction_label[0])
```

0/P:

Predicted Defaulter Label: YES

Predict Defaulter for next month data

```
# Load the dataset
df1 = pd.read_csv("/content/Defaulter_NextMonth.csv")
# Initialize the LabelEncoder
le = LabelEncoder()
# Fit the LabelEncoder on the target variable 'Defaulter'
le.fit(df1['Defaulter'])
# Selecting only the specified columns for features
selected_columns = ['IoT', 'SE', 'HS-OB', 'OE1- SC', 'OEI-ICCF', 'IOTL']
X1 = df1[selected_columns]
# Predict using the Random Forest classifier
y_pred = rf_classifier.predict(X1)
# Map predictions to 'Yes' and 'No' labels
```

```
y pred labels = ['YES' if label == 1 else 'NO' for label in y pred]
# Assign predicted labels to the 'Defaulter' column
df1['Defaulter'] = y pred labels
# Save the DataFrame back to the CSV file
df1.to csv("/content/Defaulter NextMonth.csv", index=False)
print(df1["Defaulter"])
0/P:
\cap
      NO
1
      NO
2
      NO
      NO
4
     NO
    . . .
72
      NO
73
     NO
74
      NO
75
     YES
76
      NO
Name: Defaulter, Length: 77, dtype: object
```

Logistic regression is also giving wrong output

```
from sklearn.linear_model import LogisticRegression

# Load the dataset

df2 = pd.read_csv("/content/drive/MyDrive/ML datasets/DefaulterList -
Sheet1 (1).csv")

# Encode the target variable

le = LabelEncoder()

df2['Defaulter'] = le.fit_transform(df2['Defaulter'])

# Selecting only the specified columns for features
selected_columns = ['IoT', 'SE', 'HS-OB', 'OE1- SC', 'OEI-ICCF', 'IOTL']

X = df2[selected_columns]
y = df2['Defaulter']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# Initialize the Logistic Regression classifier
logistic regression = LogisticRegression()
# Train the classifier
logistic_regression.fit(X_train, y_train)
# Evaluate the classifier on the test set
y pred = logistic regression.predict(X test)
print("Classification Report on Test Set:")
print(classification report(y test, y pred))
# Define the student's attendance data for prediction
student attendance = {
    'IoT': 10,
    'SE': 10,
    'HS-OB': 10,
    'OE1- SC': 12,
    'OEI-ICCF': 0,
    'IOTL': 0
# Convert the student's attendance into DataFrame
student df = pd.DataFrame([student attendance])
# Predict whether the student is a defaulter or not using Logistic
Regression classifier
defaulter prediction = logistic regression.predict(student df)
# Convert the predicted label back to the original label
defaulter prediction_label = le.inverse_transform(defaulter_prediction)
print("Predicted Defaulter Label:", defaulter prediction label[0])
0/P:
Classification Report on Test Set:
            precision recall f1-score support
          0
                 1.00
                          0.88
                                     0.93
                                                  16
                 0.00 0.00
                                     0.00
                                      0.88
                                                  16
   accuracy
```

macro	avg	0.50	0.44	0.47	16
weighted	avq	1.00	0.88	0.93	16

Predicted Defaulter Label: YES

Implementing the KNN model

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report

# Initialize the KNN classifier
knn_classifier = KNeighborsClassifier(n_neighbors=5)

# Train the classifier
knn_classifier.fit(X_train, y_train)

# Predictions on the test set
y_pred = knn_classifier.predict(X_test)

# Evaluate the classifier
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

0/P:

Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	23
1	1.00	1.00	1.00	1
accuracy			1.00	24
macro avg	1.00	1.00	1.00	24
weighted avg	1.00	1.00	1.00	24

5) Conclusion:

By analyzing attendance data across multiple subjects, our predictive model successfully identifies students at risk of defaulting on academic obligations. Leveraging a threshold of defaulting in at least 3 subjects to determine overall defaulter status, our system provides actionable insights for educators to intervene and support at-risk students effectively, ultimately promoting academic success and retention.

6) References:

Random Forest Algorithm in Machine Learning
Random Forest Regression in Python
K Nearest Neighbors with Python | ML
Logistic Regression in Machine Learning
Matplotlib Tutorial