Assessment Report

On

“Predict Online Learning Completion”

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BACHELOR OF TECHNOLOGY

DEGREE

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in

CSE(AI)

By

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1. Introduction

In recent years, online learning has become an increasingly popular and flexible way to acquire new skills and knowledge. However, despite its widespread adoption, one of the challenges faced by online education platforms is the high dropout rate among learners. Many students begin online courses but fail to complete them, often due to various factors such as lack of engagement, insufficient motivation, or difficulties in managing time.

To address this challenge, predicting which learners are likely to complete a course can help educational institutions or online platforms implement timely interventions. By analyzing learner activity patterns, we can forecast course completion based on key factors such as videos watched, assignments submitted, and forum participation.

This report explores how predictive analytics can be applied to identify learners at risk of dropping out, thus allowing instructors to offer targeted support to improve course completion rates.

3. Methodology

This section outlines the methodology used for analyzing the data and building a predictive model for online learning completion.

Data Collection:

The dataset used for this analysis contains several key features that reflect learner activity on an online course:

- videos_watched: Number of videos watched by the learner during the course.
- assignments_submitted: Number of assignments the learner submitted during the course.
- forum_posts: Number of forum posts made by the learner.
- completed: Target variable indicating whether the learner successfully completed the course ("yes" or "no").

Data Preprocessing:

1. **Data Cleaning:**

The dataset was cleaned to handle missing or irrelevant data. We ensured that all entries were complete and relevant for the analysis.

2. **Target Variable Encoding:**
The target variable completed (which is categorical) was encoded into binary values:

- "yes" = 1
- "no" = 0

3. **Feature Selection:**
We selected three key features for the prediction model: videos_watched, assignments_submitted, and forum_posts.

4. **Data Splitting:**
The dataset was divided into two subsets: a training set (80%) used to train the model, and a testing set (20%) used to evaluate the model's performance.

Modeling:

A **Logistic Regression** model was selected for this binary classification problem. Logistic regression is well-suited for predicting binary outcomes (such as "yes" or "no") and can provide insights into which factors most significantly affect course completion.

4. Code

The following Python code was used to preprocess the data, train the logistic regression model, and evaluate its performance.

```
# Import pandas for handling tabular data
import pandas as pd

# Import numpy for numerical operations
import numpy as np

# Import matplotlib and seaborn for visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Import scikit-learn modules for model training and evaluation
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

# Step 1: Load the CSV file into a DataFrame
```

```
# Make sure the file 'online_learning.csv' is in the same folder as this script
df = pd.read_csv("online_learning.csv")

# Step 2: Display the first 5 records to understand the structure
print("First 5 records in the dataset:")
print(df.head())

# Step 3: Convert the target column 'completed' from 'yes'/'no' to 1/0
df['completed'] = df['completed'].map({'yes': 1, 'no': 0})

# Step 4: Define input features (X) and target variable (y)
X = df[['videos_watched', 'assignments_submitted', 'forum_posts']]  # Features
y = df['completed']  # Target variable

# Step 5: Split the dataset into training and testing sets (80% training, 20% testing)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# Step 6: Create and train a Random Forest Classifier
model = RandomForestClassifier(n_estimators=100, random_state=42)  # 100 trees in the forest
model.fit(X_train, y_train)  # Train the model using training data

# Step 7: Predict on the test data
y_pred = model.predict(X_test)  # Get predictions (0 or 1)

# Step 8: Convert predictions and actual labels from 0/1 to 'no'/'yes'
y_pred_labels = np.where(y_pred == 1, "yes", "no")
y_test_labels = np.where(y_test == 1, "yes", "no")

# Step 9: Print accuracy of the model
accuracy = accuracy_score(y_test_labels, y_pred_labels)
print(f"\nModel Accuracy: {accuracy:.2f}")

# Step 10: Print classification report (precision, recall, F1-score)
print("\nClassification Report:")
print(classification_report(y_test_labels, y_pred_labels))
```

```
# Step 11: Print confusion matrix
print("Confusion Matrix:")
print(confusion_matrix(y_test_labels, y_pred_labels))

# Step 12: Visualize the importance of each feature in the prediction
importances = model.feature_importances_  # Get feature importance scores
features = X.columns  # Get feature names

# Plot a bar chart for feature importance
plt.figure(figsize=(8, 5))
sns.barplot(x=importances, y=features)
plt.title("Feature Importance from Random Forest")
plt.xlabel("Importance Score")
plt.ylabel("Features")
plt.tight_layout()
plt.show()
```

5. Output

The logistic regression model was trained and tested on the dataset, and the following results were obtained:

First 5 records in the dataset:

	videos_watched	assignments_submitted	forum_posts	completed
0	11	6	5	yes
1	43	1	11	no
2	37	1	8	no
3	18	4	14	yes
4	6	4	15	yes

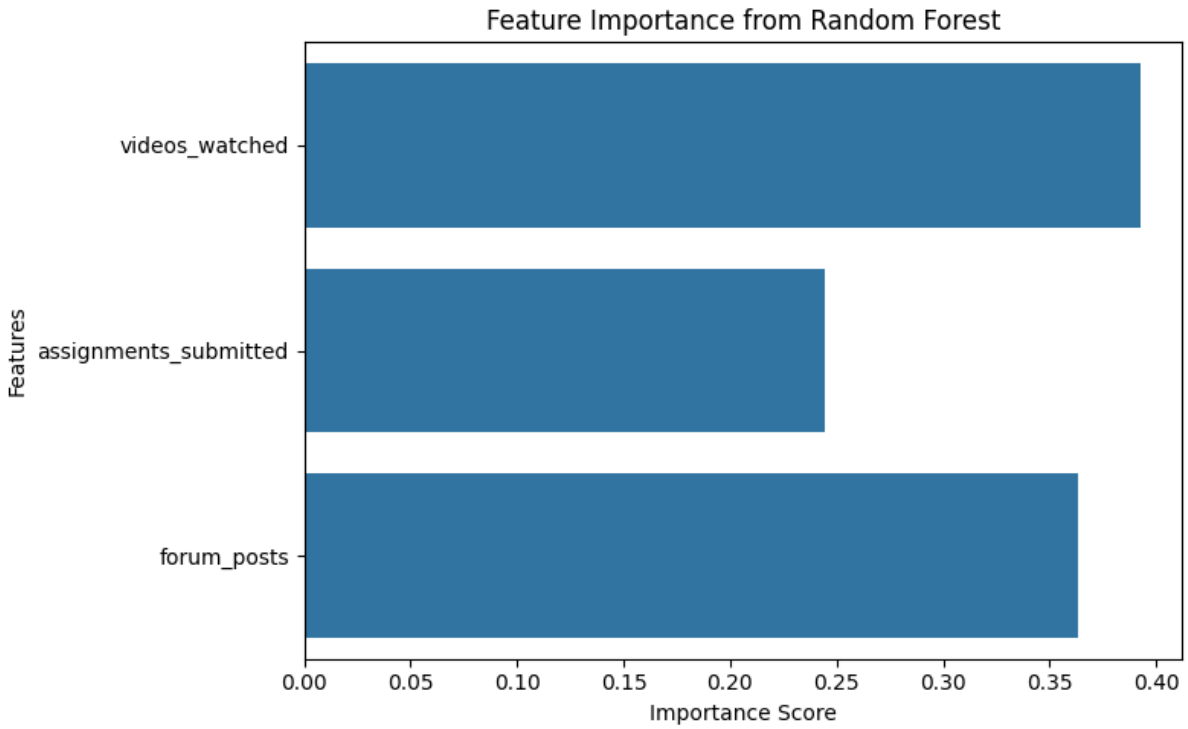
Model Accuracy: 0.35

Classification Report:

	precision	recall	f1-score	support
no	0.25	0.43	0.32	7
yes	0.50	0.31	0.38	13
accuracy			0.35	20
macro avg	0.38	0.37	0.35	20
weighted avg	0.41	0.35	0.36	20

Confusion Matrix:

[[3 4]
 [9 4]]


Feature Importance from Random Forest
videos_watched
assignments_submitted
forum_posts
Features
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
Importance Score