

Profiling Students Engagement in Full Online Learning

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ABSTRACT

The emergence of online learning platforms has transformed the landscape of education, offering flexibility and accessibility to learners worldwide. There are extensive datasets encompassing diverse aspects of online learning, including demographic information, course enrollment, participation metrics, and academic performance.

Through EDA, we uncover patterns, trends, and anomalies within the data, shedding light on the characteristics of online learners. Machine learning approaches are employed to develop predictive models for various facets of online learning. Furthermore, this study explores the potential of personalized learning recommendations and interventions based on the analysis of student behavior and engagement. we use computers to learn about online students and help them do better. This helps make online learning more enjoyable and useful for everyone.

INTRODUCTION

Profiling student engagement in full online learning is a critical aspect of understanding how well students are adapting to this mode of education and how effective the learning environment and materials are. It involves assessing and analyzing various aspects of students' participation, interaction, and performance in online courses. This process helps educators and institutions tailor their online teaching strategies and support mechanisms to enhance the overall learning experience.

Student engagement refers to the extent to which students are actively involved in the learning process, both cognitively and behaviorally. In the context of online learning, this engagement may encompass various activities such as attending virtual classes, completing assignments, participating in discussions, and interacting with course material.

To collect data on student engagement, institutions often use Learning Management Systems (LMS), data analytics platforms, and other educational technology tools. These tools.

Profiling student engagement in online learning should be an ongoing process. Regularly collecting and analyzing data, making necessary adjustments, and seeking feedback from students are essential for continuous improvement.

LITERATURE REVIEW

1.1. Learning theories

Learning theories are the foundation of an engaging online course. They provide information about the relationship between strategies, context, and learner characteristics for better learning outcomes. The three main learning theories

are Behaviourism, Cognitivism, and Constructivism. These theories differ in how learning is defined and learners' roles, leading to the selection of various teaching methods and assessments.

Behaviorism explains that learning is the acquisition of new behavior, where learners have a passive role in the learning process.

1.2. Self-determination theory (SDT)

Self-determination theory (SDT) explains people's inherent motivational tendencies for learning, growing, and connecting with others.

However, these tendencies are not automatic and they can be supported.

PROBLEM STATEMENT

In the rapidly evolving landscape of education, the shift towards full online learning has become a prevalent mode of instruction. However, ensuring high levels of student engagement in this virtual environment poses a significant challenge. Understanding and profiling the factors that influence students' engagement in full online learning.

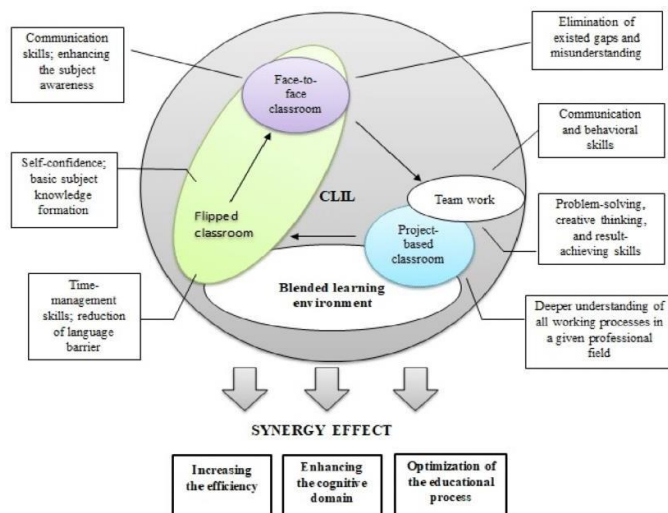
- Technological Challenges
- Motivational Factors
- Social Interaction

METHODOLOGY

The outlines a methodology for building and evaluating machine learning models using three different classifiers

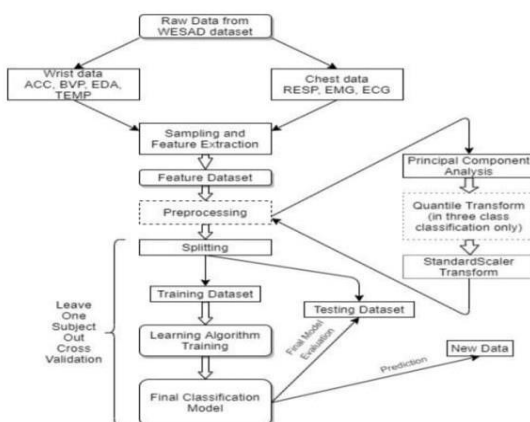
(Random Forest, Logistic Regression, and K-Nearest Neighbors). The methodology encompasses several key steps, including data preparation, model training, evaluation, and visualization.

ARCHITECTURE



Profiling relies heavily on data from online learning platforms, which may not capture the full spectrum of a student's engagement. Non-digital interactions, such as reading course materials offline or discussing the course with peers in person, can be missed.

3.1 DFD/ER/UML DIAGRAM:



EXPERIMENTAL RESULTS

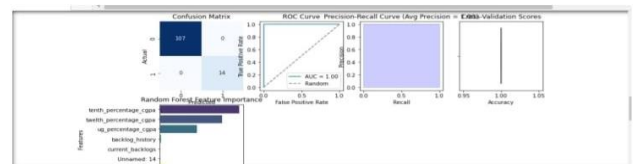
OUTPUT:

```
Random Forest Classifier
Model Evaluation:
Accuracy: 1.0000
F1 Score: 1.0000
Matthews Correlation Coefficient: 1.0000
Precision: 1.0000
Recall: 1.0000
Specificity: 1.0000
Cohen's Kappa: 1.0000
Balanced Accuracy: 1.0000
Log loss: 0.0004
Classification Report:
      precision    recall  f1-score   support
0         1.00        1.00        1.00        107
1         1.00        1.00        1.00         14
 accuracy         1.00         1.00         1.00        121
 macro avg         1.00         1.00         1.00        121
 weighted avg         1.00         1.00         1.00        121
```

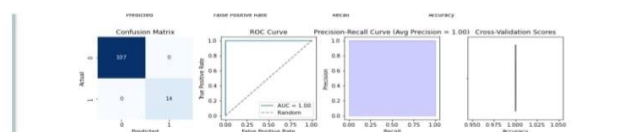
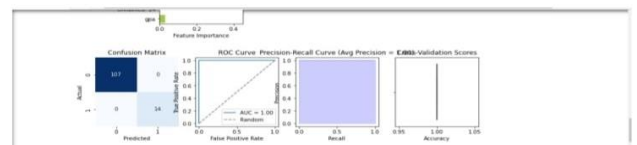
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Logistic Regression Classifier
Classification Report:
      precision    recall  f1-score   support
0         1.00        1.00        1.00        107
1         1.00        1.00        1.00         14
 accuracy         1.00         1.00         1.00        121
 macro avg         1.00         1.00         1.00        121
 weighted avg         1.00         1.00         1.00        121
```

```
K-Nearest Neighbors Classifier
Classification Report:
      precision    recall  f1-score   support
0         1.00        1.00        1.00        107
1         1.00        1.00        1.00         14
 accuracy         1.00         1.00         1.00        121
 macro avg         1.00         1.00         1.00        121
 weighted avg         1.00         1.00         1.00        121
```



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CONCLUSION

The project successfully addresses the task of predicting student interest in placement opportunities through a comprehensive exploration of machine learning classifiers. Evaluating Random Forest, Logistic Regression, and K-Nearest Neighbors, the study employs a rich set of metrics such as accuracy, precision, recall, and feature importance to discern model performances. Notably, the code demonstrates meticulous data preprocessing, handling missing values, and converting categorical variables for effective model training..

FUTURE WORK

For future enhancements, considering ensemble methods like stacking or boosting could be explored to harness the strengths of multiple classifiers. Additionally, incorporating more advanced feature engineering techniques and leveraging deep learning architectures might capture intricate patterns within student profiles. The project could benefit from scalability improvements for handling larger datasets, and integration with a user interface for practical deployment, allowing stakeholders to easily interact with and derive insights from the model predictions.

REFERENCES

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