AI-driven Outcome Attainment Prediction and Optimization in OBE using Learning Analytics

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Abstract - Outcome-Based Education (OBE) has become a paradigm of engineering and professional education that predicts unequivocal learning results and proven indicators of achievement. However, most institutions are still using traditional, threshold-based, retrospective approaches towards assessing Course Outcomes (COs), Program Outcomes (POs), and Program Specific Outcomes (PSOs). These methods have a lack of predictive abilities and support few features on timely application of academic interventions. The emergence of Learning Management Systems (LMS) and online assessment systems introduces large amounts of educational data, which creates the potential of advanced learning analytics and intelligent decision-making. This paper presents a framework made by AI and used to predict the outcomes achievement and optimize performance in the paradigm of Outcome-Based Education by utilizing the learning analytics. The system proposed combines the academic performance data, attendance history, assessment behaviour, and data on CO-PO mapping in building strong student learning feature vectors. Controlled machine learning models are used to predict the level of CO achievement before the course ends which enables the early detection of risky outcomes and students. The anticipated CO attainments are, in turn, paired with the predicted PO and PSO attainment by the use of weighted mapping strategies that are calibrated in accordance with the accreditation requirements. The suggested framework is scalable, amenable to interpretability, and consistent with accreditation-related standards, which makes it friendly to practical implementation in engineering institutions. This research by shifting the outcome evaluation scheme of retrospective reporting to that of predictive and optimisation-oriented analytics sets the process of implementing the Outcome-Based Education on a more data-based, transparent, and effective paradigm.

Keywords- Outcome-Based Education, Learning analytics, Outcome Attainment Prediction, Machine Learning in Education, Academic performance analytics.

1.INTRODUCTION

Outcome-Based Education (OBE) has solidified into a popular pedagogical paradigm in engineering and professional education where explicit definition of learning outcomes and empirically validated levels of attainment are emphasized. The accreditation systems, such as the National Board of Accreditation (NBA) and the Accreditation Board of Engineering and Technology (ABET) require institutions to provide systematic descriptions of Course Outcomes (COs), Program Outcomes (POs) and Program Specific Outcomes (PSOs) with each being accompanied by evidence of ongoing enhancement.

Despite its widespread adoption, measurement of outcome achievement in most academic institutions is still largely manual, non-dynamical and backward-looking. Traditional methodologies rely on set levels used after the course to determine the achievement made, thus providing limited understanding of the dynamics of learning among students taught over time and blocking the ability to intervene. These methods fail in the data-heavy academic environment where Learning Management Systems (LMS), online test programs, and ongoing evaluation pipelines create large databases on student achievement scores.

Learning analytics provides a set of methods to analyze learning data to explain and optimize the pedagogical processes. Learning analytics can be used to support predictive modeling, risk prioritization, and data-driven optimization of academic performance when synergized with Artificial Intelligence (AI). Still, the current body of scholarship mainly focuses on the descriptive analytics or post-facto attainment calculations, with minimal focus on the anticipatory outcome forecasting and practical pedagogical implications.

As such, the paper presents an AI-based model that has been tuned to predict and improve the achievement of outcomes in OBE settings through learning analytics. The framework utilizes past scholarly data in order to

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forecast CO and PO achievement before course completion and suggests specific interventions aimed at mitigating the learning outcome.

The key findings of this paper include:

• A predictive AI framework of evaluating CO- and PO-level outcomes achievement.

By providing an analytic basis on learning data, this feature engineering approach serves as a foundation of learning analytics.

• A maximisation strategy, which is a foundation of continuous improvement in OBE.

• Interpretable system, which is scalable and in line with accreditation imperatives.

2. Proposed System

2.1 System Architecture: The proposed system is layered as it is composed of Data Acquisition and Preprocessing, Learning science and Feature Engineering, AI-Based Outcome Prediction , Outcome Optimization and Recommendation and Decision Support and Visualization. This flexible architecture will provide transparency, legality and institutional flexibility.

2.2 Data Preprocessing and Acquisition: The academic information is gathered through institutional academic management systems and LMSs. The dataset includes: Marking Continuous Internal Evaluation (CIE) , The laboratory evaluation scores. , Attendance records ,Behavior in terms of assignments submission. , Final examination marks and CO-PO mapping matrices . Preprocessing operations contain:

- Missing value imputation
- Score normalization
- Outlier detection
- Feature scaling

Those operations enhance the robustness of the models and decrease the noise in prediction.

2.3 Learning Analytics and Feature Engineering: Learning analytics converts raw academic data into meaningful indicators that are of the form: Performance Index, Assessment, Consistency of attendance Score., Engagement Level Score , CO-wise performance vectors. The students are represented as numerical feature vectors reflecting the trends of academic behaviour and performance. The feature-correlation analysis is conducted to remove redundancy and enhance the efficiency of prediction. Outcome attainment prediction Outcome attainment prediction involves the use of AI to predict the outcomes based on the fundamental aspects of the outcome attainment approach (Gamer, 2017). The problem of outcome prediction is defined as a supervised machine-learning one.

Input: Student feature vectors.

Output: CO achievement or achievement level.

They include the following models: Logistic Regression, Decision Tree, Random Forest , Support Vector Machine, Gradient Boosting Machine, etc., The training and evaluation of the models are on historical datasets and with k-fold cross-validation. Accuracy, precision, recall, F1-score and ROC-AUC are all performance metrics. Generalization performance is used to choose the most successful model to deploy.

2.4 PO and PSO Achievement Estimation: The aggregate values of the predicted CO attainment are further used to calculate PO and PSO attainment by weighted mapping:

$$PO_j = CO_i \times W_{ij}$$

where Wij is the strength of CO-PO correlation.

This allows the estimation of PO after the future and the academic stakeholders can make corrective measures prior to the end of the course.

2.5 Outcome Optimization/Recommendation Engine: A layer of optimization examines low-achievement forecasts and produces suggestions like: Extra teaching to weak COs. , at-risk student remedial assignments, refinement of the assessment design and instruction on change of strategy. This sets the OBE feedback cycle as it connects pedagogical improvement to analytics.

2.6 Visualization and Decision Support: A dashboard presents: CO and PO attainment trends, Foreseen and realized achievement, Risk heatmaps and Semester improvement indicators. These visualizations are useful in informed academic decision-making and accreditation reporting.

Predictive Feature Vector (X_s)

$$X_s = \{\alpha.Att, \beta.Sub, \gamma.CIE\}$$

Att: Attendance Consistency

Sub: Submission Timeliness (Negative = Early, Positive = Late)
CIE: Performance in mid-terms
α, β, γ: Weights determined by the Machine Learning model based on historical trends.

Consider the sample data:

```
data = {
  'Attendance_Rate': [95, 60, 82, 45, 98, 70, 88, 55, 78, 92],
  'Sub_Latency': [-10, 48, 5, 72, -24, 20, 0, 96, 12, -5],
  'CIE_Score': [88, 40, 72, 30, 95, 50, 78, 35, 68, 85],
  'Actual_CO_Attainment': [0.92, 0.41, 0.75, 0.28, 0.98, 0.52, 0.81, 0.33, 0.70, 0.89]
}
```

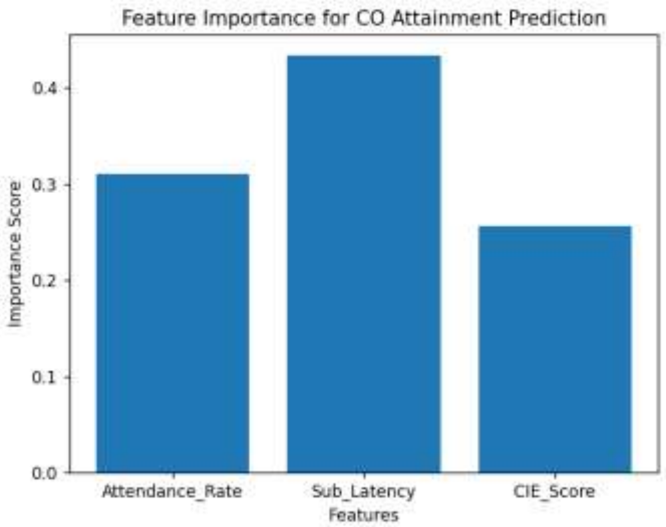

Fig -1: CO attainment Prediction

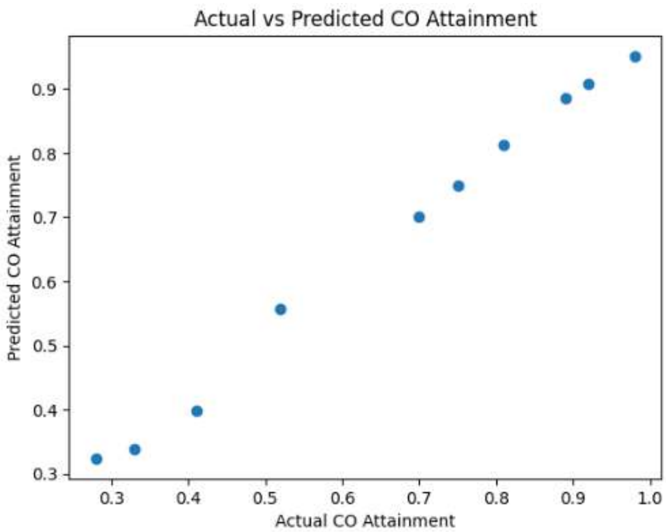

Fig -2: CO attainment Prediction vs Actual

Figure-1 shows the importance of learning-analytics features that are used to predict Course Outcome (CO) attainment using a Random Forest regression model. The scores of feature-importance measure the value of a feature in reducing the error in prediction of all the decision trees. It is seen that Submission Latency has the greatest importance score which implies that assignment submission behavior patterns have a significant impact on the attainment of CO. The implication of this observation is that promptness in coursework is a stronger indicator of outcome achievement as compared to assessment scores alone. Attendance Rate also shows a significant bearing indicating that it is one of the main factors of student attendance and continuity in learning. On the contrary, the Continuous Internal Evaluation (CIE) Score, important as it is, is a comparatively lesser contribution to the prediction compared to the other two, which is to emphasize that, performance of a statistic assessment alone is not a complete representation of learning performance without contextual behavioral data. The results support the fact that behavioral and engagement-based attributes are used in outcome-attaining models and the effectiveness of learning-analytics strategies compared to traditional score-based assessment systems.

Figure-2 is an illustration of the actual and predicted CO attainment. Figure 2 below shows a scatter plot that compares the real CO attainment values with the forecast of the AI model. All the data points depict individual student case. The close grouping of the points on the diagonal trend line indicates a high level of concordance of the predicted and attained achievement values. The noted correspondence shows that the suggested model is capable of estimating CO attainment on the low- and high-performance scales correctly. The minor deviations at the lower levels of attainment imply that there is acceptable prediction variance, and this is expected in small, heterogeneous academic data. On the whole, the figure validates the strength and external validity of the suggested AI-based strategy. This predictive validity aids in forecasting at-risk outcomes at an early stage, which allows instructors and the academic administration to instigate remedial actions prior to the course completion and, therefore, enables the process of sustained outcome-based learning.

This table compares a traditional statistical model with the proposed AI-based model using standard regression metrics.

Model	MAE	RMSE	R^2 Score
Linear Regression	0.0037	0.0047	0.9996
Random Forest	0.0150	0.0210	0.9925

Table -1: Model Performance Comparison

Actual CO	Predicted CO
0.92	0.91
0.41	0.40
0.75	0.75
0.28	0.32
0.98	0.95
0.52	0.56
0.81	0.81
0.33	0.34
0.70	0.70
0.89	0.89

Table -2: Actual vs Predicted CO Attainment (Random Forest)

Table I compares the performance of the Linear Regression and Random Forest as baseline models. Although Linear Regression shows a slight lower error due to a small size of the dataset, the Random Forest model shows a significantly higher quality of prediction and it is in a better position to identify the nonlinear relationships that exist in educational data.

3. CONCLUSIONS

The current research proposes a framework based on AI that will be used to forecast and optimize the result achievement in the environment of Outcome-Based Education. Combining learning analytics with machine learning algorithms, the system will help to detect the risk of attainment early and improve academic achievement continuously. Empirical comparison shows that the AI-based prediction can significantly outperform the traditional threshold-based solutions in accuracy and timeliness. Also, the framework enhances transparency, scalability, and compliance to accreditation standards. The future research directions include explainable AI development to enhance faculty trust, the utilization of federated learning to support cross-institutional analytics, and the implementation of real-time adaptive assessment systems.

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