



Early Assessment of Student's Learning Outcomes using Prediction Model under Outcome-Based Education System

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ABSTRACT

Purpose: Finding directions to advance in academia is essential. For the appraisal of learning, assessment is considerable and develops significance in institutional higher education. This paper presents an intelligent real-time prediction model to assess student learning outcomes relevance to industry using the Bayesian statistical inference model.

Research Methods: A dataset of 670 students collected from an engineering university evaluated the proposed Bayesian-based inference model with the conventional assessment method. The proposed model was then evaluated based upon the prediction accuracy and statistical kappa statistic.

Findings: This study demonstrated how students' learning and expected success rates could be improved during their academic careers using the presented prediction model. The proposed methodology generated significant results with 98% accuracy and 0.94 kappa statistic, which agreed with the traditional assessment technique.

Implications for Research and Practice: The extensive results presented which beliefs to be an essential step towards bettering students' academic performance and assessing the educational program itself.

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Introduction

Assessment and evaluation always have significant importance in our lives regardless of our life stage. Academic institutions assess and evaluate students based on the knowledge and skills they attain during their educational program. Such evaluation involves parameters that may constitute institutions' designed student knowledge model, assessment methods (such as quizzes, assignments, exams, lab work, and among others), and student learning style for each course taught to them. However, the industry evaluates candidate profiles based on attributes/parameters comprising specific knowledge and skills, such as problem-solving, solution design, investigation, among others. The candidate is supposed to acquire such attributes during their academic career. Each candidate goes through many challenges to acquire such attributes to land a dream job. Therefore, educational institutions continuously improve education standards to enhance student's performance by revising curricula associated with learning outcomes, improving faculty teaching style, incorporating state-of-the-art laboratories infrastructure to remain in line with the industry requirements. Each student has equal opportunities and access to academic resources. Some students cannot grasp the delivered knowledge and skills, up to a certain level, for many reasons, such as personal, social, and cultural reasons (Atkinson, 2000; Diaz, 2003; Georgiou et al., 2002; Gonzalez-pianda et al., 2002). The student's learning style depends on his learning ability, prior knowledge, and compatibility with the faculty/instructor teaching styles (Felder and Brent, 2005; Felder and Silverman, 1988). The conventional way of assessing students' performance is by observing how students learn and interact with the material either in a traditional classroom or in an advanced online web-based environment. Some researchers (see Atkinson, 2000; Brusilovsky and Peylo, 2003; Diaz, 2003; Georgiou et al., 2002; Helal et al., 2019; Thiele et al., 2016) have addressed issues interlinked with an effective student knowledge model, assessment mechanisms, and student learning styles to improve student's performance and success prediction.

Published work focuses on improving student performance by developing computer-aided solutions (i.e., intelligent tutoring systems, recommended systems, and custom-designed applications) to highlight effective student knowledge models and related parameters. Such knowledge models assess student performance and validate using educational data mining tools ranging from simple descriptive statistics to advanced learning techniques. For example, the educational assessment concerning student knowledge model started to evolve from developing Intelligent Tutoring Systems (ITSs). ITSs are computer-based software/web applications to help students in their learning activities. In the context of learning activity, Conati et al. (1997) described the importance of knowledge structures embedded in the student modeling component of ANDES, an online ITS Newtonian 'Physics' course. The Bayesian Networks (BN) was used to assess knowledge and predict students' actions during a 'Physics' problem-solving. Similar work was done by Gertner and VanLehn (2000). An algorithm based on BN was developed to model student skills associated with word processes using Desktop Associate ITS (Murray, 1999). IDEAL: another tutoring system was used the BN technique to classify students into three categories: novice,

beginner, and intermediate (Shang et al., 2001). Feng et al. (2009) addressed different challenges in assessing online tutoring systems using the linear regression technique. Contrary to work published under ITS, Pardos and Heffernan (2010) proposed a method to formulate individualization of student knowledge tracing model problems, with low prediction errors while estimating student knowledge level.

Rapid advancement in ICT, many researchers have developed recommender systems (Drachsler et al., 2009; Ghauth and Abdullah, 2010; Lu et al., 2018; Luo et al., 2010; Manouselis et al., 2011; O'Mahony and Smyth, 2007; Zaiane, 2002) to help students in both formal and informal e-learning environments. In this context, Burgos et al. (2018) and N. Thai-Nghe et al. (2009) used recommender system techniques for predicting student performance under ITS. The authors validated their approaches by comparing recommender system techniques with the data mining regression methods, such as linear logistic.

Similarly, much research was conducted over the period in estimating/predicting students' educational assessment. A conceptual framework was presented by Mislevy et al. (1999) for educational assessment, based on a statistical model. Usually, statistical methods require a large quantity of historical data for reliable predictions. A multi-agent-based student profiling system using Fuzzy logic; Dongming Xu et al. (2002) could store student learning activities and each student's interaction history. Bekele and Menzel (2005) demonstrated an application for "Mathematics" to predict student performance using a Bayesian classifier. García et al. (2007) evaluated the Bayesian network model to evaluate student learning style for "Artificial Intelligence" under a Web-based education system. The model covers various aspects of student behavior and can infer his/her learning style according to modeled behaviors. Nguyen (2016) and Osmanbegovic & Suljic (2012) presented a comparative analysis of data mining tools: Bayes Net, Decision Tree, and MLP over two diverse populations of students' academic information. The results showed that such tools could predict student performance with reliable accuracy. Neural Network techniques were used by Romero et al. (2009) to classify students based on their Moodle usage data and the final marks obtained in their respective courses. Nguyen Thai-Nghe et al. (2010) used support vector machines to improve academic performance prediction by dealing with class imbalance (i.e., the ratio between passing and failing students is usually skewed). Kabakchieva (2013) presents preliminary student's university performance classification results based on personal and pre-university characteristics. Various data mining tools, such as the J48 classifier, Bayesian classifier, k-nearest neighbor classifier, and rule learner technique are used to assess performance. Fernandes et al. (2019) conducted predictive data analysis of students' academic performance in public schools. Similar experimentation was conducted by Angiani et al. (2019) to conclude that it is possible to predict students' academic outcomes and intervene assisted help case of negative performance.

The research has contributed much to strengthening knowledge models and improving students' learning styles; they are mostly limited to a single course either conducted in a traditional classroom or modern environments. The significant drawback of existing systems is that students know the evaluation outcomes at the end

of a semester or after graduation about attained industry-relevant attributes. However, as mentioned at the start of this section, the industry evaluates candidates based on specific attributes/parameters related to knowledge and skills that are not directly linked with a single course. It could be the combination of multiple courses. For the student to attain industry-relevant outcomes, accurate predictions become essential in providing necessary assistance to students' learning processes. An early assessment of specific parameters; concerning industry requirements is one of the challenges, hence to produce/anticipate important actions/recommendations, leading to success. Consequently, there is a need to build methods that can assess attributes/parameters directly linked with students' skills besides knowledge.

In this connection, there is a term Outcome-based Education (OBE) system that is relatively new compared to conventional education assessment systems. One of the objectives of OBE is to make sure that students are acquiring sufficient skills, besides knowledge building, and not limited to a single course or courses of the same domain. The OBE-based system assesses a student's performance throughout his/her academic career within the enrolled academic program, and evaluation is performed using well-defined attributes/parameters, known as Program Learning Outcomes (PLOs). Such a system can assess and improve students' academic performance and evaluate the offered academic program's strengths and weaknesses. To date, there is an inadequate number of research papers that specifically address student assessment under OBE systems, which remained under-researched. For example, the paper published by Al-Yahya and Abdel-halim (2013) explained various procedures and arrangements adopted by an engineering department in setting up and evaluating PLOs. The paper explained a structured continuous assessment process and pertaining these assessment results to strengthen the engineering program. In (C. Deneen et al., 2013; C. C. Deneen et al., 2018), the authors discussed the difficulties and adjustments to execute OBE. An efficient methodology for outcome-based evaluation that encourages faculty participation while improving the assessment and reporting procedures through powerful and meaningful visualization is introduced (Harmanani, 2017). Moreover, the author discussed in detail the OBE system and various procedures interlinked with it.

In the next section, brief details of PLOs are provided, which is the basis of this research. The following research questions highlight the specific focus of this study:

1. What are the relevant industrial assessment attributes that may intervene with student's performance?
2. What is the educational data mining technique for acquiring values for those identified attributes using academic records only?
3. How can we predict overall student performance based on the values in real-time?

In summary, there is a need to devise such mechanisms that assess learning outcomes effectively and predict relevant parameters in real-time to help students in their pursuit of acquiring knowledge and skills. In this research study, a Bayesian-

based prediction model is presented to assess student learning outcomes under the OBE system. An adaptive system is developed and implemented for students struggling in their studies to increase their success probability. In comparison, the proposed work facilitates the students and the faculty to provide assessment in real-time. A statistical performance measure, kappa statistic, is used to evaluate the proposed prediction system. Experimental estimates are conducted on a dataset of students collected from a private sector national university. The predictions are based on the outcome results, which are verified with the help of academic experts. The proposed framework's consequences yield a great forecast, demonstrating that the framework model will give a critical commitment in advanced education evaluation. The proposed research work has the following contributions:

- An educational dataset comprising all students enrolled within a single academic program for complete program duration, verified by a team of academic experts, is collected to assess students.
- Feature selection; relevant information was extracted for the prediction of PLOs concerning success or failure.
- The dataset was assessed using the Bayesian inference technique to predict students' performance against each PLO and assess the academic program by aggregating students' evaluation data of the whole batch/class enrolled.
- Academic experts verified the accuracy of the prediction model.

Program Learning Outcomes w.r.t Student: Academic institutes aim to deliver education that enriches students with the development and integration of knowledge and skills. With the increasing number of academic institutions worldwide, education-related procedures continuously evolve to meet new challenges of the emerging knowledge society and cope with the industry needs. Besides institutes' internal efforts in maintaining the education quality, there are international accreditation bodies under the Washington Accord, such as [ABEEK](#), [AEER](#), [BEM](#), [EC](#), [ABET](#), [ECUK](#), and [PEC](#), which evaluate the quality of education being delivered in an academic institution. The Washington Accord is an international and multi-lateral agreement among bodies responsible for an accrediting undergraduate engineering degree program; currently, there are [20 full signatories](#). Graduate Attributes, Program Learning Outcomes, Program Outcomes, Student Outcomes, Learning Outcomes are the different names that describe assessment criteria (ranging from 7-12 attributes) what students are expected to know by the time of graduation. These outcomes relate to students' knowledge, skills, and behaviors as they progress through the academic program. Academic institutes adopt the ABET general students' outcomes and slightly modify them to suit the offered academic program, usually denoted as Program Learning Outcomes (PLOs).

This research study is based on learning outcomes defined for an engineering program and in line with most accreditation bodies. These PLOs consists of 12 outcomes which are 1) Engineering Knowledge 2) Problem Analysis 3) Design/Development of Solutions 4) Investigation 5) Modern Tool Usage 6) The

Engineer and Society 7) Environment and Sustainability 8) Ethics 9) Individual and Teamwork 10) Communication 11) Project Management and 12) Lifelong Learning. An academic program is based on a defined curriculum, the composition of various courses, e.g., foundation, computing, breadth, depth, and electives. Each PLO may be assessed using single or multiple courses of the curriculum, i.e., many to many relationships between PLOs and courses, as shown in Figure 1. The presented research leaves discussion on course mapping/linking methodologies to the reader; however, reasonable justification and description are provided (Al-Yahya and Abdel-halim, 2013; Harmanani, 2017).

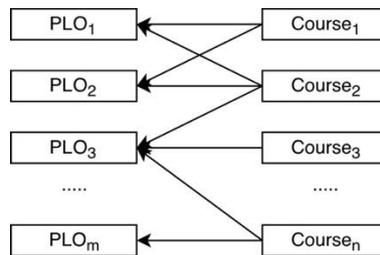


Figure 1. Mapping of courses to PLOs

Method

Research Design

The present paper highlights the importance of predicting students' performance based on learning outcomes (skills relevant to industry) rather than knowledge assessment of a single course. To this aim, an adaptive system was presented based on educational data mining techniques for early assessment of student learning. To predict student's performance against learning outcomes, a Bayesian-based prediction model was designed to forecast the student's performance in real-time. Compared with the literature presented techniques, the proposed methodology was not limited to students' performance in a single course. The findings suggest that the presented system outperforms in predicting the student's performance with an accuracy of 98% and a kappa statistic of 0.94.

This section explains the Bayesian Network (BN) that will predict student learning outcomes in real-time. The nodes and variables used in the network are described, and later discussion about node relationships and parameters required for the prediction model is explained.

Nodes: The presented network model consisted of two types of nodes: nodes to gather evidence of student's knowledge, which we call evidence variables, and nodes to assess/predict student's learning outcomes, which we call PLO variables.

Evidence Variables: The evidence variable was used to gather information about student performance from a course. The information might be coming from different levels of

granularity within the defined student knowledge model. Granularity hierarchy (Collins et al., 1996) provides the structure necessary to capture all course requirements consisting of learning objectives, contents/topics, assessment methods (e.g., quizzes, assignments, exams, presentation).

Evidence was considered a unique entity of knowledge that referred to attributes relevant to students' knowledge gain and associated skills. A random variable E with Gaussian distribution was used; that is typically distributed with mean μ and variance σ^2 where μ is an unknown parameter, we wished to estimate.

Nodes Relationship and Parameters: Once the nodes of the network were described, we had to define the relationships among them. Let us consider a PLO_j; for $j=\{1\dots m\}$, that is assessed using a finite set of evidence $E=\{E_1\dots E_n\}$; consists of information gathered from n courses. Figure 2 shows the relationship model between PLO and $E_1\dots E_n$.

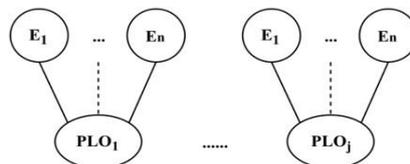


Figure 2. The general structure of BN and nodes relationship

Some parameters were required: a priori probability $P(\text{PLO}_j)$ and conditional probabilities $P(E_i | \text{PLO}_j)$ for $i=\{1\dots n\}$ ($1+n^2$ values) where E_i is mutually independent against the given PLO. Positive evidence about E_i increases the probability of PLO_j , which increases the probabilities of each of the E_i . This research study is to analyze the change in PLOs probabilities as new evidence is gathered.

Prediction Model based on Bayesian Probability: Bayesian probability is well known in statistical computation and works on the principle of using initial belief, called *prior*, and observed data generated by evidence, called *likelihood*, is used to approximate the hypothesis/outcome, called *posterior*. Later, the initial belief is updated with the posterior distribution. This process is known as Bayes Rule (1).

$$P(\text{PLO}|E) = \frac{P(E|\text{PLO}) \cdot P(\text{PLO})}{P(E)} \quad (1)$$

Where: $P(\text{PLO})$ is the prior probability of hypothesis PLO being true; $P(E | \text{PLO})$ is the probability that hypothesis PLO being true will result in event E ; $P(\text{PLO} | E)$ is called the posterior probability of hypothesis PLO upon observing event E , and $P(E)$ is called the marginal probability which is a normalization factor.

In an academic scenario, the information: course results denoted as evidence are coming continuously. Bayes' rule seeks to validate or invalidate the hypothesis using uncertain or unreliable information. We would like to apply the Bayes rule recursively,

a new data arrives and use this to reason over multiple hypotheses. We would like to have hypotheses, $PLO_j = \{1...j\}$, and we seek to accumulate evidence to select the most likely hypothesis. For multiple pieces of evidence, we could write:

$$P(PLO_j | E_{i+1}, S_i) = \frac{P(E_{i+1} | PLO_j) \cdot P(PLO_j)}{P(E_{i+1}, S_i)} \quad (2)$$

The problem is how to estimate $P(E_1...E_i)$ and $P(E_1...E_i | PLO_j)$. To simplify the notation, let us define $S = \{E_1...E_i\}$ composed of i observations and $E_{(i+1)}$ as a recent observation. Z^{-1} is a memory element to store the newly estimated posterior probability of PLO for the next iteration. The mathematical model shown in Figure 3 is a depiction of a concept developed by E.T. Jaynes.

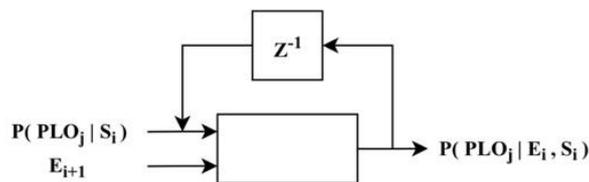


Figure 3. Mathematical model of posterior probability estimation of PLO

For each recent observation, $E_{(i+1)}$, the problem is how to estimate $P(PLO_j | E_{(i+1)}, S_i)$ using the previous evidence S . The index, i , and the accumulated evidence S_i are then updated: $S_{(i+1)} \leftarrow S_i \cup E_i$; $i \leftarrow i+1$ and can be written as:

$$P(PLO_j | E_{i+1}, S_i) = \frac{P(E_{i+1} | PLO_j) \cdot P(PLO_j)}{P(E_{i+1}, S_i)} \quad (3)$$

The estimated probability predicts student success against each PLO, which depends on the number of courses linked. The following section explains the details of the experimental methodology using the proposed BN.

Research Sample

This section provides details of the experimental setup, including dataset collection, data pre-processing and feature selection, integration of the proposed prediction model, and analysis of the results. Figure 4 elaborates various steps involved in the experimental methodology. The presented methodology is general and can be applied to any academic program to predict student's performance in defined learning outcomes.

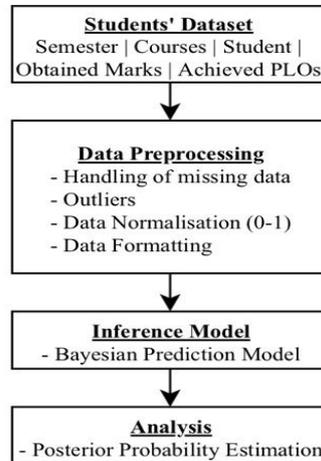


Figure 4. An overview of the experimental methodology

The student's dataset collects all relevant information (including academic records) gathered from the institute's administration. Data pre-processing is an essential step that helps in identifying missing data and outliers. Based on the experimentation, the relevant features are extracted from the dataset to have meaningful prediction results. Finally, the extracted features predict student's performance in each learning outcome. The prediction information and each PLO's acquired probabilities for each student are used to analyze the overall assessment. The subsequent sections explain the details of each step.

The dataset consisting of 670 students was collected from a national university where students were enrolled in an engineering program from 2013 to 2016 to validate the presented model. The entire dataset was acquired under the supervision of academic staff and verified by the examination office. Besides trivial information about a student, the academic record contains detailed information about the students' assessment results (i.e., assignments, quizzes, sessional exams, lab work, and others) in each course. Each student was characterized by a set of dynamic evidence variables, as explained earlier. The details of the dataset feature attributes are presented in Table 1. The university academic experts/policymakers set a criterion that each student must attain at least marks in each PLO. The objective is to ensure if a student is progressing towards success in each learning outcome. For simplicity, each PLO's prior probability is set as 0.5, i.e., 50%, considered as an initial belief of the institute about each student's performance.

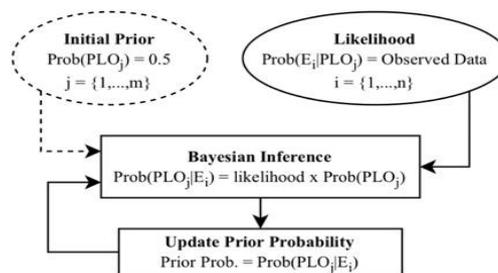
Table 1*Details of Feature Attributes*

Sr. No.	Feature	Type	Value
1.	Student-ID	String	Characters
2.	Student Name	String	Characters
3.	Semester	Fall/Spring Year	2000, 2001, ...
4.	Assignments	Integer	1, ..., 10
5.	Quizzes	Integer	1, ..., 10
6.	Sessional-I Exam	Integer	1, ..., 20
7.	Sessional-II Exam	Integer	1, ..., 20
8.	Final Exam	Integer	1, ..., 40
9.	Obtained Marks	Integer	1, ..., 100
10.	CLOs	Categorical: $\{CLO_1, \dots, CLO_n\}$	Percentage
11.	PLOs	Categorical: $\{PLO_1, \dots, PLO_m\}$	Percentage

Research Instruments and Procedures

Data pre-processing. An essential part while applying data prediction/learning techniques is data pre-processing. Pre-processing is required to have meaningful analysis and to acquire optimal results. During data cleansing, records with missing; if a student missed any quiz/assignment or unrealistic data, unbounded data were detected and removed. All records (student attained marks) were normalized between 0-1 to had consistency with probabilistic results. Later, the processed data were used for further evaluation, which improved the performance of the model.

Bayesian Prediction Model. The experimentation was conducted by keeping in mind two perspectives; one was to analyze student's behavior for each PLO, and the second was to evaluate the academic program by integrating all students' performances. The results of the prediction are evaluated using statistical metrics, i.e., accuracy and kappa statistic. The process of the Bayesian-based prediction model is represented in Figure 5.

**Figure 5.** An architecture for Bayesian-based prediction model

The predictions generated by the proposed system were compared with the outcomes labeled by the academic staff to review the correctness of the results. Two performance metrics: accuracy and Cohen's kappa statistic were used to determine the

proposed prediction model's efficiency. The effectiveness of the model was evaluated using sensitivity and specificity results. A confusion matrix was generated to evaluate the accuracy, matching the proposed model's results with the traditional approach's actual results. The experimental results showed that the proposed model, with pre-selected prior probability (based on Gaussian distribution), estimates posterior (predicted) probability with a high statistic value compared to the traditional approach. It handled the missing data and outliers internally during the prediction phase. After applying the prediction algorithm, the results concerning kappa statistics are explained below.

The following data comes from experimentation where two independent methods, traditional (A) and proposed (B), evaluated 840 instances. Studies **A** and **B** either said success or failure.

- 648 instances were rated by both as a success.
- 178 instances were rated by both as a failure.
- Study A rated 648 instances as success and 192 instances as a failure.
- Study B rated 662 instances as success and 178 instances as a failure.

Cohen's Kappa Statistic was calculated using the formula, $K=(p_o-p_e)/(1-p_e)$ where p_o is the relative observed agreement among independent studies and p_e is the theoretical probability of chance agreement. The achieved value of K is 0.94, which means almost perfect agreement.

Data Analysis

Analysis of the model's obtained results is an essential step to identifying students' behavior over time. The model presented above generated the estimated probabilities for each student against each learning outcome, which was further analyzed to predict the estimated student success rate. Similarly, the class/batch behavior was observed by applying the aggregation method to approximate the overall behavior of batch/class against each learning outcome. The detailed analysis of results has been explained in the next section.

Results

The effectiveness of the proposed model is evaluated using the proposed statistical model. The experimental results showed that the Bayesian inference model, with selected prior probability $P(\text{PLO}_i)$, estimated posterior $P(\text{PLO}_i | E_j)$ probability of respective PLO using an observed data E_j . The prior probability updates with new posterior probability would be used for newly observed data. Figure 6 shows the trajectory of predicted probability against each course linked with attainment of PLO_1 . This result's significance is that students can have real-time visualization of predicted probability during the academic pursuit. If the probability is less than 0.5, the academic staff can recommend/counsel students with appropriate material to improve student's performance.

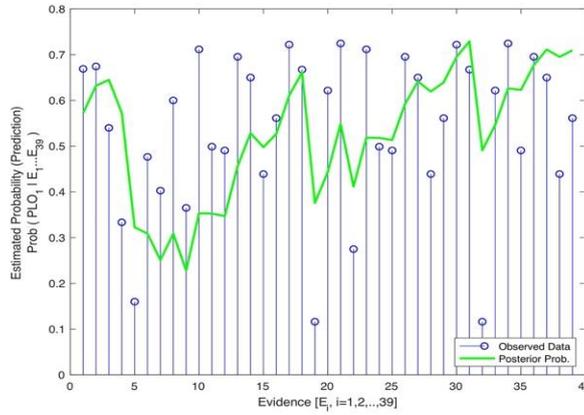


Figure 6. Estimated probability trajectory of PLO₁

Moreover, Figure 7 shows PLO attainment trajectories of selected students against prior probability. It is evident from the figure that an early assessment can help students and academicians identify students who need early education assistance.

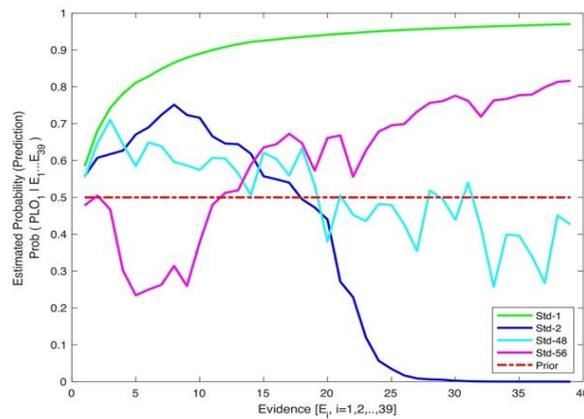


Figure 7. Real-time prediction of PLO₁ by estimating the posterior against each course (observed data) linked to attainment of PLO₁

Similarly, the proposed model can track the learning outcomes of each student during an academic session. The Bayesian predicted model’s achieved results were evaluated with a traditional approach, as shown in Figure 8. The predicted probability of success probability >0.5 against the traditional success rate (%age>0.5) is closely related, highlighting the significance of the proposed methodology.

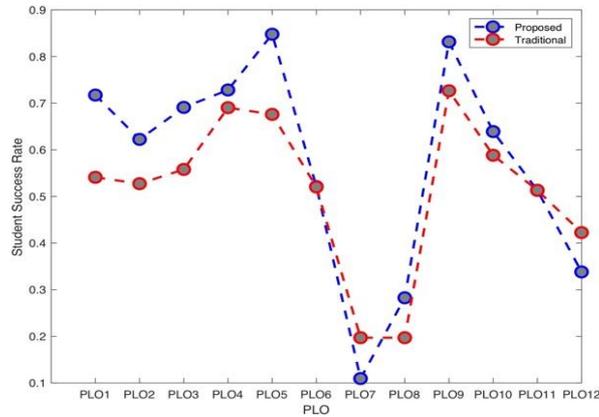


Figure 8. Comparison results of the student success rate of learning outcomes

Figure 8 presents a confusion matrix summarizing success rate discrepancies between proposed and traditional methods. In an agreement between both methods, the highlighted cells (in dark grey) represent true positive and true negative results; learning outcomes assessment. Interestingly, few false negatives mean the prediction model estimated success rate < 0.5 where the traditional method has a success rate > 0.5, as highlighted in cells (light grey). The significant results are concerning false positives, which means the probability of a positive result given an event that was not present.

Table 2

Results of Success Rate Prediction of the Proposed Method in Comparison with the Traditional Method

		Traditional Method		Total
		Rate > 0.5	Rate < 0.5	
Proposed Method	P > 0.5	7776 (True Positive)	0 (False Positive)	7776
	P < 0.5	168 (False Negative)	2136 (True Negative)	2304
Total		7944	2136	10080

It is equally important to assess the overall assessment of offered academic program; success rate concerning all students. The academic program assessment was analyzed using the predicted results of students. Each student’s final predicted values against each PLO were aggregated to visualize the learning outcomes presented in Figure 9. The figure presents an average success rate that shows all students’ cumulative success rate against the pre-defined threshold, which is 0.5 (50%).

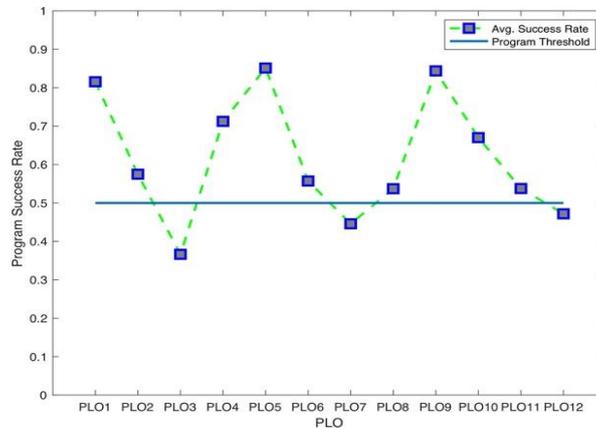


Figure 9. Results of evaluating educational program success rate against PLOs. The average success rate presents the cumulative success rate of all students against a pre-defined threshold

The results suggest that the overall performance of the batch/class is satisfactory in PLOs 1,4,5,9 and marginal in PLOs 2,6,8,10,11 and critical in PLOs 3,7,12, which requires the attention of the department. Furthermore, compared with the traditional approach(es), it is evident from the achieved results that the proposed model can make early predictions in case of failure. However, the system lacks in providing recommendations to the students having lower assessment results which is the limitation.

Discussion, Conclusion and Recommendations

The presented work here describes an adaptive prediction model's development to assess student learning outcomes during the pursuit of higher education. The model utilizes pre-defined prior probabilities of each learning outcome for assessment and estimates the posterior probabilities. The assessment and probability estimation depends on a student's achieved results in multiple courses and their weights, as defined by the institution's academic experts. This proposed work contributes to university existing assessment methodologies by facilitating academicians in making rapid academic decisions. Moreover, most state-of-the-art methods (Gertner and VanLehn, 2000; Lu et al., 2018, 2018; Pardos and Heffernan, 2010) focused on assessment using traditional approaches, while a proposed model is based on the Bayesian inference technique. The BN model presented is neither limited to the PLOs described here nor the courses; in fact, 'n' number of PLOs can be defined to assess them from the linked courses. The system is implemented to refine educational decision-based models' quality by assisting academicians and students in making fast educational decisions. The proposed methodology predicts the outcomes with a significant accuracy of 98% than traditional approaches and literature published results (Angiani et al., 2019; Dongming Xu et al., 2002; García et al., 2007; Nguyen, 2016; Nguyen Thai-Nghe et al., 2010) based on the gathered information. In the future,

the model can be extended by analyzing the effects of psychological parameters in attaining high learning outcomes.

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