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Student Outcomes Assessments Using Deep Learning

Abstract: - The pursuit of academic accreditations for degree programs is a common objective among universities worldwide. This objective is driven by the recognition that accreditation not only enhances the quality of teaching within the institution but also facilitates the recruitment of highly qualified faculty members and students. In fact, accreditation has become a near-universal requirement for universities across the globe. Even ABET, the accrediting body primarily responsible for institutions in the United States, has expanded its scope to include programs on a global scale. A significant portion of the documentation submitted to accreditation agencies pertains to the collection and reporting of data on student achievement of course learning outcomes (CLOs), Program Learning Outcomes (PLOs), and Key Performance Indicators (KPIs). Given the advancements in big data and the recent progress in data mining and machine learning, it is imperative to establish a methodology for data reporting and an automated evaluation system to effectively measure performance indicators. This research paper proposes the utilization of an intelligent system based on the Artificial Neural Networks (ANN) model to assess the ABET-defined Student Outcomes (SO) through the classification of their associated Key Performance Indicators (KPIs) at the program level. The proposed model employs deep learning techniques with the Multilayers Perceptron classifier (MLP) and comprises four layers: the input layer, two hidden layers, and the output layer. The findings presented in this paper serve as a proof of concept for the feasibility of an intelligent system that can generate meaningful data relevant to the accreditation process, regardless of the size of the academic department.

Keywords: Deep learning, Multilayers Perceptron, Assessment Tool, Student Outcomes, Key Performance Indicators.

I. INTRODUCTION

Accreditation has become an essential requirement for universities and their departments, playing a crucial role in ensuring ongoing access for students. Additionally, it serves as a vital tool in attracting highly qualified faculty and students. Furthermore, the acquisition and maintenance of accreditation, whether at a national or international level, often determine the allocation of government funds to universities, establishing a significant connection between financial support and accreditation status.

The primary measure for evaluating the quality of a university lies in the academic accomplishments of its students. This metric forms the foundation for universities to assess the effectiveness of their teaching, measure learning outcomes, and make informed decisions in student selection [1]. In response, educational institutions, including colleges and higher education establishments, have implemented various learning management systems that track different aspects of student learning, generating a wealth of educational data. Educational Data Mining has emerged as a rapidly advancing scientific field that offers the ability to analyze and extract valuable insights from this vast amount of data.

Within this field, numerous statistical algorithms have been successfully applied to address various challenges in educational contexts [2]. Deep networks, which are a subset of artificial neural networks (ANN), have shown significant success in addressing key educational issues. These include automated feature extraction [3], predicting student performance [4-7], and forecasting student dropout [8-10]. Importantly, ANN methods have gained considerable attention in educational research, demonstrating their usefulness in Educational Data Mining [11]. In addition to performance prediction, ANN has also proven beneficial in addressing practical concerns such as course scheduling challenges [12].

Over the past seven years, the Engineering Department has implemented a novel approach to teaching and learning, which is based on the evaluation scheme adopted from ABET. The evaluation process involves measuring the Course Learning Outcomes (CLO) that are related to the attributes that students are expected to acquire upon completing the course. To assess these outcomes, a combinational approach is employed, which includes mapping classroom activities such as quizzes, assessments, projects, and assignments to the CLOs [13]. Each CLO is then mapped to one or more Key Performance Indicators (KPI), and the final results of the CLO evaluation, described by the Performance vectors, are used to determine the student outcomes [14],[15]. This approach has been instrumental in enhancing the quality of teaching and learning at the program level [16].

The assessment of Student Outcomes (SOs) has been made mandatory for all engineering programs. However, the traditional SOs appraisal paradigm followed by many engineering programs has resulted in ambiguous assessment methods that failed to deliver successful continuous improvement. The biggest concern was the lack of specific

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parameters to assess the SOs. To address this issue, a set of KPIs has been used to assess the SOs. KPIs are measurable attributes that allow us to identify the performance needed to achieve the desired results. In this research, a new model has been proposed to assess each SO via the classification of its associated KPIs. Deep learning techniques and data processing with MLP classifier were used in this research. To evaluate the classifier, parameters such as accuracy, error rate, recall, and precision were considered.

The literature review carried out is discussed in the next section, and section III discusses the methodology and the proposed strategies. Detailed experimental outcomes are shown in Section IV, with sufficient discussion, and accompanied by a conclusion in Section V.

II. LITERATURE REVIEW

As outlined by ABET, Student Outcomes (SOs) encompass the knowledge that students are expected to acquire and effectively apply by the time they graduate. These outcomes are associated with various domains of learning, including cognitive abilities, communication skills, and knowledge acquisition, which students develop throughout their academic journey [17], [18]. Assessment, on the other hand, refers to a set of processes aimed at collecting, identifying, and organizing data to evaluate the achievement of different SOs. To ensure effectiveness, assessment methods employ quantitative, qualitative, direct, or indirect measures to gauge the outcomes [19-20]. Key Performance Indicators (KPIs) are utilized as a collection of measurable attributes to assess student outcomes. These indicators enable us to determine the level of performance required to meet the desired outcomes [21]. The mapping of Course Learning Outcomes (CLOs) to SOs is facilitated through the use of KPIs. ABET explicitly emphasizes the importance of evaluating the extent to which student outcomes are achieved through the assessment process [22]. Various approaches exist for assessing CLOs, including the average, threshold, and performance vectors approaches. In a combined approach, all three methods are considered collectively. In the average approach, it is expected that the average score of students surpasses the predetermined success criteria. Conversely, the threshold approach focuses on a high percentage of students exceeding the reference success criterion. Lastly, the performance vector approach, developed by Miller et al. [23], employs a scoring rubric to assess performance. This approach formulates a 4-tuple vector, known as the EAMU vector, based on the assignment's processing data. The vector categorizes performance into four levels: Excellent (demonstrating flawless application of knowledge), Adequate (making conceptually insignificant errors and minor procedural errors), Minimal (involving conceptual errors), and Unsatisfactory (indicating a lack of understanding or application of knowledge). [24-25].

Table I: EAMU Vector

Category	Score		weights
Excellent	>	0.9	3
Adequate	>	0.75	2
Minimal	>	0.66	1
Unsatisfactory	<	0.66	0

The EAMU vector is used to measure the performance of CLOs at the course level [26]. Since this paper focuses on assessing SOs at the program level, two new vectors were used, the Course-Vector and the KPI-Vector. The Course-Vector consists of four attributes (GPA, Status-Flag, U-flag, and Threshold-Average).

- The EAMU vector's GPA is determined by calculating the average, this average is computed using the weights provided in Table 1.
- The class of the EAMU vector is indicated by the Status-Flag, the EAMU vector is categorized into four groups (R, Y, W, and G) based on the Flagging Heuristic explained in table 2 below.
- The Threshold-Average represents the proportion of students with a score above 80 compared to the total number of students.
- The U-Flag is set to true if the percentage of failing students exceeds 20%; otherwise, it is false.

Table II: Flagging Heuristic for classifying the EAMU vectors

Status-Flag	Specifications
Red Flag (R)	EAMU vector average is below 1.80, and the “Unsatisfactory” portion of the vector exceeds 20%
Yellow Flag (Y)	EAMU vector average is below1.80, or the “Unsatisfactory” portion of the vector exceeds 20%, but not both
White Flag (W)	Any EAMU vector that does not fall under the Red, Yellow, or Green Flag classifications.
Green Flag (G)	EAMU vector average is at least 2.75 with no indication of any “Unsatisfactory” performance.

The KPI-Vector consists of four attributes (N_R, N_Y, N_W, N_G), where the attributes represent the Number of Red-Flags, Yellow-Flags White-Flags, and Green-Flags assigned to that KPI during the past semesters.
At the end of every semester, the KPI-Vector of a particular course will be updated by Status-Flag and stored together with Course-Vector in the Performance Vector Table (PVT) as illustrated in the flowchart in figure 1, which describes the necessary steps to assess the student's outcomes (SO).

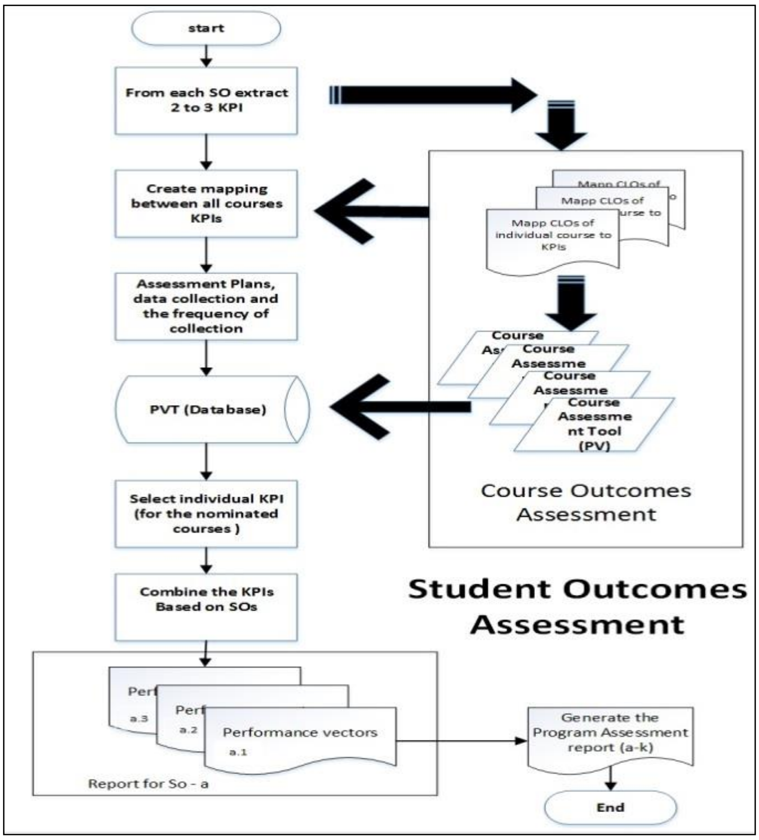

Figure 1. Processes of Student Outcomes Assessment

The process commences with the extraction of 2 to 3 Key Performance Indicators (KPIs) from each Student Outcome (SO). Subsequently, all Course Outcomes (CO) of program courses are aligned with the identified KPIs, which are, in turn, linked to the respective SOs.
A periodic assessment plan is employed to systematically collect data. Utilizing this comprehensive information, a program assessment report is generated for each SO, involving the individual classification of its KPIs. The categorization into "Below," "Meet," and "Above" is determined based on the attributes of the Course-Vector connected to the specific KPI and its associated KPI-Vector, which incorporates historical KPI data.
The Artificial Neural Network (ANN) is a powerful and dynamic modeling technique used to model nonlinear functions [27]. It consists of artificial neurons that mimic the connections between neurons in the human brain [28-29]. The ANN supports three different learning techniques: supervised, unsupervised, and reinforcement learning. It has been successfully applied in various domains, such as predicting students' perceptions in music education [30] and automatically categorizing academic researchers' bibliometric profiles to identify common trends among institutions [31]. The ANN excels in neural fitting, prediction, and data classification with high accuracy. Therefore, it has been proposed as a valuable tool for assessing the Key Performance Indicators (KPIs) associated with Student Outcomes (SOs). In this study, a dataset of historical data from Engineering departments, specifically prepared for ABET accreditation, is utilized to ensure accurate prediction of academic performance. The ANN model serves as a framework and tool to evaluate yearly academic performance, identify obstacles in the learning process, and continuously enhance educational quality.
The objectives of this paper comprise the following:

- Develop a classification model for the KPIs using deep learning.
- Assessment of the SOs that are associated with the classified KPI.
- The methodology for reporting data of the closing loop procedure using the developed model to identify opportunities for improvement at the program levels.

III. METHODOLOGY

In this paper, a supervised learning technique is proposed; the algorithm learns from a labeled dataset, providing information that the algorithm can use to predict the new data label.

3.1 Problem Statement

In this part, we present the mathematical notations and define the problem. Each academic program consist of a set of m courses denoted C= {c_1, c_2, c_3….c_m}, the courses are mapped to set of n key performance indicator (KPIs) denoted by K= {k_1, k_2, k_3…. k_n}. For each course c_i mapped to KPI k_j, the system will have Semester-collected information that can be represented as course vector V_{ij} = {GPA_{ij}, U_{ij}, TH_{ij}, F_{ij}}, where GPA_{ij} represents the average GPA of the scores, U_{ij} represent the course unsatisfactory flag, TH_{ij} represent the percentage of the students above the threshold, and F_{ij} represent the Status-Flag in course c_i that is mapped to KPI k_j. The system is assumed to have historical data for each KPI vector k_j in the form of a vector L_j = {R_j, Y_j, W_j, G_j}, where R_j, Y_j, W_j, G_j represents the number of Red-flag, Yellow-flag, White-flag and Green-flag assigned to the KPI k_j for the past years. For each KPI k_j we represent their outcomes as KPI-class ϑ_j, assuming there can be three outcomes such as "Above", "Met", and "Below". With the given notations listed above, we seek to learn a model $\beta\ (\dots,\dots|x)$ having parameter x such that it can classify the KPI outcomes class ϑ as follows:

$$f\big(V, L, \vartheta, \beta\ (\dots,\dots|x)\big) \rightarrow \overline{x} \tag{1}$$

Where f is denoted the learning process, V is used to represent the course vector, L represent the KPI vector, ϑ represent the KPI class and the learned parameter of $\beta\ (\dots,\dots|x)$ are given by $\overline{x}$.

Then we can use the trained model $\beta\ (\dots,\dots|x)$ as follows for making the output classification $\overline{\vartheta}$ on a new set of course vector $\overline{V}$ with the associated KPI vector $\overline{L}$.

$$\beta(\overline{V}, \overline{L}|\ \overline{x}\ ) \rightarrow\ \overline{\vartheta} \tag{2}$$

3.2 Model

The present study intends to implement an intelligent educational system using the ANN model to assess the Student Outcomes via the classification of the KPIs by using deep learning with an MLP classifier. MLP is a strong nonlinear statistical model consisting of several layers of nodes, each layer being completely linked to the next one. There are three distinct layer types: input, hidden, and output.

The output of the neural model can be obtained by the mathematic equation below:

$$P = f\big(b + \textstyle\sum_{i=1}^{m} Wi(a)i\ \big) \tag{3}$$

Where P is the output, (a)i are the inputs, m is the number of input nodes, Wi are the summation weights, f is the activation function, b is a bias.

The hidden layer may consist of one or more hidden layers, and, technically, there is no fundamental research about how many hidden layers are necessary for such a network. The hidden layers ultimately decide the network size, which means that the greater the network size, the more time it takes to train the network [32]. The proposed model consists of four layers: an input layer, two hidden layers, and an output layer, as illustrated in figure 2 below. The input layer consists of eight nodes, the hidden layers with five and three nodes, respectively, and three nodes for the output layer.

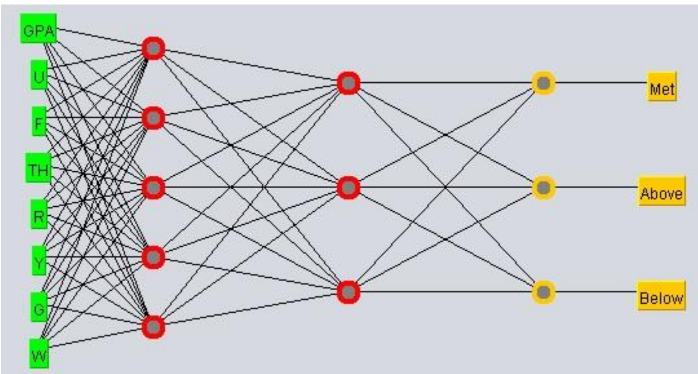

Figure 2. ANN model using MLP classifier

3.3 Data Set

The dataset was obtained from the Engineering program over ten years. The dataset is represented by two vectors, the Course-Vector, and its associated KPI-Vector; the course vectors consist of GPA_{ij}, U_{ij}, TH_{ij}, F_{ij},.

Table 3: Dataset attributes

Variable	Description	Value
GPA	Course average GPA	0-4
U	Course unsatisfactory flag	0 |1

F	Course Status flag	1|2|3|4
TH	Course percentage of students above 80 %	0-100%
N_R	Number of Red flags assigned to KPI during the past semesters	Number
N_Y	Number of Yellow flags assigned to KPI during the past semesters	Number
N_G	Number of Green flags assigned to KPI during the past semesters	Number
N_W	Number of Weight flags assigned to KPI during the past semesters	Number

The dataset is segregated into two sets: training and testing data. Traditionally, the train/test ratio is distributed at 50/50, 60/40, or 70/30. However, in this study, the dataset was partitioned with an 80/20 ratio. To meet the requirements of Multilayer Perceptron (MLP), which necessitates normalized input data, z-score normalization was applied before training the algorithm and testing the data, following equations 4, 5, and 6.

$$Z = \frac{S-\mu}{\sigma} \quad (4)$$

Where Z is the z-score and s is the row value, σ is the Standard Deviation value, and μ is the Mean value.

$$\mu = \frac{1}{m}\left(\sum_{i+1}^{m} S_i\right) \quad (5)$$

$$\sigma = \sqrt{\frac{1}{m}\left(\sum_{i=1}^{m} (S_i - \mu)^2\right)} \quad (6)$$

Table III: Sample of the normalized dataset

GPA	U	F	TH	N_R	N_Y	N_G	N_W	Class
0.93	0.00	0.67	1.00	0.00	0.50	0.50	0.00	Above
0.93	0.00	0.67	1.00	0.25	1.00	0.38	0.57	Met
0.45	0.00	0.33	0.51	0.75	0.50	0.25	0.14	Below
0.62	0.00	0.00	0.79	0.50	0.25	0.25	0.71	Met
0.71	0.00	0.00	0.89	0.00	1.00	1.00	0.43	Above
0.65	0.00	0.00	0.95	0.25	0.00	1.00	0.86	Above
0.34	1.00	1.00	0.53	0.25	0.50	1.00	0.57	Below
0.95	0.00	0.67	1.00	0.50	0.25	0.25	0.71	Met

The selected dataset will be processed in such a way that it can be supplied to MLP classifier as input; table 3 shows a sample of the normalized dataset.

3.4 Model Evaluation

In the realm of machine learning, learning curves are frequently employed for algorithms that acquire knowledge progressively over time. These curves illustrate how effectively the model is learning by employing varying proportions of the training dataset to fit the classifier and document errors. Figure 3 depicts the Error rate versus the Percentage of training data randomly extracted, revealing an exponential trend. As the percentage of excluded data rises, so does the error rate. For instance, when 10% of the data is randomly omitted and 90% utilized, the error rate is at a minimum (2.07). As the percentage of excluded data increases, the error rate also escalates. This suggests that the model successfully addresses overfitting and underfitting challenges during the training process, rendering it reliable in this context.

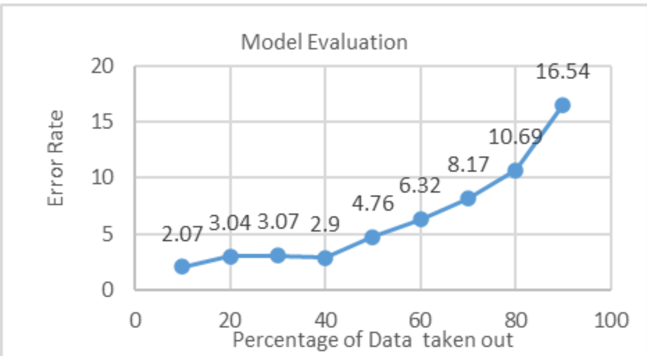

Figure 3. Model Evaluation

IV. Experimental

To assess the model, various performance parameters including accuracy, error rate, recall, and precision were considered. The dataset was divided into an 80/20 ratio for training and testing purposes. The experimental outcomes, including the confusion matrix, are presented in Table 4.

Table IV: confusion matrix

Met	Above	Below	Classes
102	1	0	Met
1	59	0	Above
0	0	122	Below

The matrix comprises nine cells organized in a three-by-three grid, categorized into four groups: True Positive (TP), denoting the count of positive Key Performance Indicators (KPI) correctly classified; True Negative (TN), representing the number of negative KPI accurately classified; False Positives (FP), indicating the count of positive KPI inaccurately classified; and False Negatives (FN), reflecting the number of negative KPI incorrectly classified. The performance parameters were computed from the confusion matrix as outlined below:

1- Accuracy represents the number of correctly classified KPIs divided by the total number of instances; the model provides a high accuracy rate (99.298 %).

$$Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+FP+TN+FN}} \quad (7)$$

2- The Error rate represents the number of incorrectly classified KPIs divided by the total number of instances; the model provides a low Error rate (0.701 %).

$$Error\ rate\ = \frac{F\mathrm{P}+F\mathrm{N}}{\mathrm{TP+FP+TN+FN}} \quad (8)$$

3- The Recall represents the number of correct classified KPI divided by the summation of True Positive and False Negative of a particular class.

$$Sensitiviy = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \quad (9)$$

4- The Precision represents the number of correct classified KPI divided by the summation of True Positive and False Positive of a particular class

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \quad (10)$$

Table 5 below shows the results of true positive rate, false-positive rate, Precision, and recall for each class.

Table V: Performance parameters using MLP

TP Rate	FP Rate	Precision	Recall	Class
0.981	0.016	0.971	0.981	Met
0.950	0.004	0.983	0.950	Above
1.000	0.006	0.992	1.000	Below

The final phase of the process involves creating an assessment report for each Student Outcome (SO) separately. As depicted in Figure 4, the report encompasses the SO description, the associated courses, and their performance vectors utilized in the assessment. The classification field indicates the projected status of the Key Performance Indicators (KPI).

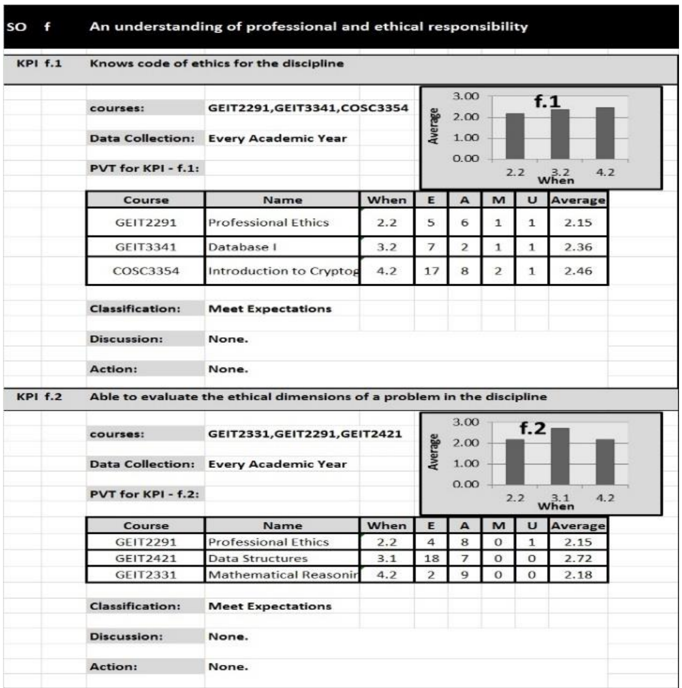

Figure 4. Student Outcomes Assessment.

V. Conclusion

The need for accreditation in Academic Institutions and Departments is progressively evolving into a mandatory requirement rather than an elective decision. In many countries, universities that do not secure and maintain accreditation may face the potential risk of closure. Accreditation not only ensures compliance but also opens doors to eligibility for government funding, scholarship programs, and other government-backed initiatives.

This research introduces a methodology for assessing Student Outcomes (SOs) in undergraduate programs by categorizing Key Performance Indicators (KPIs) using an Artificial Neural Network (ANN) model. The model is trained using historical datasets containing courses and their associated KPIs from previous years. This training serves as the groundwork for classifying the KPIs for courses offered in the current academic year, thereby evaluating the SOs. Future plans include expanding the ANN model to encompass courses like internships and final year projects, which rely on indirect measurement. Additionally, there are intentions to enhance the model to predict KPI performances for upcoming years and leverage these predictions to recommend necessary improvement measures at the program level.

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