A Predictive Model to Support Decision Making for the Accreditation of Learning Programmes using Data Mining and Machine Learning

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***Abstract*— Terabytes of data are produced by higher education institutions every year, and this data is crucial for determining how countries will develop. There are significant amounts of this Educational Data in a variety of relatively recent formats. We suggest a model for gathering, securing, and analyzing this substantial amount of data. The analysis of the data is used to evaluate the institution against a standard set by a Quality Assurance body, for the accreditation of higher education learning programmes. Therefore, the model supports the decision-making process in accreditation evaluation. The paper provides a proposed model using data mining and machine learning for the prediction of accreditation criteria, in the case of this paper the research considers academic staff appropriateness and adequacy.**

Keywords— Educational Data, Knowledge Discovery, Accreditation Process, Higher Learning Institutions (HEIs), Learning Programmes, Quality Assurance, Predictive Analytics, Machine Learning, Data Mining

I. INTRODUCTION

Accreditation is a vital tool in higher education, ensuring the quality and effectiveness of learning programs by setting standards based on the institution's operations and curriculum, thereby enabling the delivery of the best possible education [1]. Accreditation measures curriculum quality, attracts top students, and aids informed decision-making. External agencies assess higher education institutions' eligibility and meet required standards [2], [3].The traditional accreditation process, prone to human error and time-consuming, requires the development of predictive models for decision-making support [4]. These models can analyze factors and data related to higher education institutions and their learning programs, such as student performance, faculty qualifications, curriculum design, resource allocation, facilities, and program characteristics like curriculum design and industry standards [5], [6].

Implementing a predictive model in the accreditation process can provide several benefits [7]. First, it can improve the efficiency of the accreditation process by automating data collection and analysis, reducing the time and effort required for manual evaluation [8]. Second, a predictive model can enhance the accuracy and objectivity of decision-making by removing any potential bias or subjectivity associated with human judgment [9]. Additionally, a predictive model can provide early warning indicators and identify areas of improvement for institutions that may be at risk of not meeting accreditation standards [10]. Furthermore, integrating a predictive model into the accreditation process can facilitate continuous quality improvement in higher education [11].

Predictive models use machine learning and deep learning algorithms to analyze historical data to predict student performance trends and improve learning programs. This helps accrediting bodies identify at-risk institutions and provide valuable insights for decision-making in accreditation processes [12]. Further, predictive models analyzes quiz scores and program performance to identify programs with consistently below-average scores, enabling investigation into instruction quality and resource allocation for accrediting bodies. AI models are increasingly used in data analytics for forecasting, such as predicting course abandonment probabilities and predicting academic achievement based on learning behavior [13]. For instance, AI models were used to build an early alert system for identifying students with a high probability of dropping out in the first year [13]. Meanwhile, machine learning models were employed to analyze student behavioral data when participating in online learning to predict student engagement [13]. Predictive models help personalize learning experiences by analyzing student data, identifying effective activities based on progress and comprehension, enhancing engagement and motivation, and predicting university program intake [14]. In this study, we apply machine learning algorithms to cluster data and identify the data related to the learning programme under submission and the standards set in the accreditation criteria by the Higher Education Authority.

This paper is organized as follows:

In Section II we presented the related works and review of the literature. In Section III the paper considers what the study intends to achieve. Section IV of the paper discusses the results of the study. In Section V the paper presented the conclusion and recommends areas for further study.

II. LITERATURE REVIEW

This section of the paper considers literature that focuses on similar research work.

A. Accreditation Process with ABET

Academic accreditation is a quality assurance process where an educational institution is evaluated against specific standards set by an accreditation authority, often prioritizing academic programs or overall university accreditation to influence stakeholders' decisions [15], [16]. The Accreditation Board for Engineering and Technology (ABET) is used throughout the study as a running example. According to Scales et al. [17], ABET assesses academic programs based on eight criteria: students, program objectives, results, curriculum, faculty, facilities, institutional support, and improvement, requiring qualified professors, staff credentials, counseling, and faculty involvement [16]. Departments or colleges applying for ABET accreditation must submit a self-study report demonstrating completion of all requirements. The process involves four parts: creating the report, submitting it to ABET, and reviewing it [16]. ABET reviews the report and visits the department in person. In the fourth phase, the department receives an exit report, evaluating the program's readiness [16]. ABET then decides on the program's accreditation and the next accreditation cycle [16].

B. Big Data in Higher Education

Higher education institutions produce data that meets the criteria for big data [18]. A university manages several IT systems, including those for student registration, finance, human resources, and institutional research [18]. Every semester, these systems generate massive amounts of data, including unstructured and semi-structured data from students, staff, and professors, including internet traffic, activities, and sensor data, in addition to structured data [18].

Therefore, using Big Data techniques to analyze data from higher education institutions is preferable to using conventional techniques [19]. Researchers and businesses can examine vast datasets using this Big Data analysis to find important trends [19]. Further, an initiative among universities, uses big data to evaluate over 600,000 student records from 3 million course transactions. This helps identify common factors affecting academic program completion and retention, as well as at-risk students, enhancing institutions' capacity to identify areas in need of development [16].

C. Automation Framework to Assess Specifications for Academic Accreditation in Saudi Arabian Universities

Governments around the world have recently shifted their attention to higher education institutions to pay more attention to maintaining educational quality, improving learning outcomes, and establishing and encouraging the development of social and economic competencies within the nation [21]. Higher education often undergoes continuous growth, emphasizing quality policies, institutional mission practices, beliefs, and stakeholder expectations and ambitions [21]. "A process by which the officially designed external regulatory agencies, responsible at the government level, assess existing qualifications, standards, and procedures for educational institutions" is how accreditation is defined [21].

For universities in Saudi Arabia, several procedures and accreditation requirements are in place at the institutional and program levels [21]. The Commission collaborates with agencies to schedule evaluations, enabling quality assurance and self-studies, with each organization conducting a comprehensive self-study every five years. Self-appraisal scales provided by the National Academic Accreditation & Assessment Commission (NCAAA) are the models utilized as the foundation for self-studies [21].

D. Data Analytics in Higher Education: An Integrated View

This paper offers an overview of data analytics in higher education to better inform IS educators, researchers, education providers, institutional policymakers, and other educational stakeholders so they can implement and promote educational data analytics more successfully [22]. The study suggests that educational data analytics in higher education should be supported by clear distinctions and high correlations, and has developed terms like Learning Analytics (LA), Academic Analytics (AA), and Educational Data Mining (EDM) [22].

Table 1: Types of Analytics

Types of Analytics	**Level or Object of Analysis**	**Who Benefits**
Learning analytics	Course-level: social networks, conceptual development, discourse analysis, intelligent curriculum	Learners, faculty
	Departmental: predictive modelling, patterns of success/failure	Learners, faculty
Academic analytics	Institutional: learner profiles, performances of academics, knowledge flow	Administrators, funders, marketing
	Regional (Provincial): comparisons between systems	Funders, administrators
	National and international	National governments, education authorities

E. Educational data mining and learning analytics: An updated survey

Data mining in education was the subject of a previous survey that was revised and refined and published in this journal in 2013 [23]. This text explores the use of Educational Data Mining and Learning Analytics in education, highlighting advancements in the field over the past decade, with related terms like Academic Analytics, Institutional Analytics, Teaching Analytics, and Educational Data Science [23]. Academic program activities such as courses and degree programs, as well as research, student fee revenue, course evaluation, resource allocation, and management, are collected, analyzed, and visualized as part of institutional analytics (IA), which aims to produce institutional insight [23].

III. METHODOLOGY

Our knowledge discovery framework, which is built on a data science model, is presented in this next section.

Academic analytics, according to the theory put forth by Barneveld, Arnold, and Campbell [24], concentrates on institutional and faculty-level management, where educational data is crucial to supporting operational and financial decision-making. Additionally, according to Siemens and Long [25], academic analytics can address system comparisons to the advantage of educational donors, administrators, authorities, and governments. The model aids academics and staff in accreditation by enhancing data collection, analysis, confidence in reports, and decision-making through educational Big Data tools, ensuring accurate measurement and analysis of results.

In this study, we proposed the Knowledge Discovery in Educational Data for Accreditation Processes at the Higher

Education Authority, to take into consideration staff alignment, course burden, and staff moonlighting in the accreditation criterion. The model is a component of the HEA-IMIS used in higher education that is utilized by the Higher Education Authority to automate the accreditation process. As illustrated in Figure 1, the HEA-IMIS gathers data about institutions, learning programmes, educational initiatives, teaching methods, academic staff, various institutional documentation, etc.

Further, we suggested the Educational Data Mining with Academic Analytics (EDM/AA) model of support system, which includes all of the aforementioned components of data management and information. The model serves as the framework for the higher education institution information systems (Fig. 1). Information systems gather data on study programs, students, professors, scholarly publications, and online course integration without requiring content or number of systems.

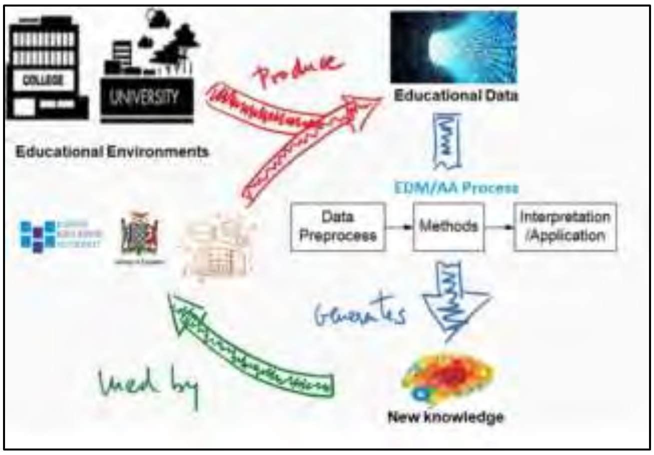

Figure 1: The proposed data science model

In this study the proposed model is implemented based on the following accreditation criterion, staff alignment, course workload and staff moonlighting. Further detail on the implementation is give the following section.

A. Data Preprocess

At this stage, it is decided where the data will be stored, how the data will be used, and whether the information gathered is appropriate for the goal. The process of feature selection entails reducing the number of variables that are utilized to forecast a specific result. The objective is to make the model easier to read, to simplify it, to make algorithms more efficient at computing, and to prevent overfitting. The educational data provided by the Higher Education Institution (HEI) shall include but not limited to bio data, academic data, qualifications, work and academic experience, specialization, assigned courses, among other data. The information needs for the model are further defined for the data collection such as staff workload, staff alignment and staff moonlighting to ensure the objective is achieved.

B. Methods

Model Design and Implementation

The study used various methods to predict academic staff appropriateness and adequacy, including General Linear Model, Logistic Regression, Fast Large Margin, Deep Learning, Decision Tree, Random Forests, Gradient Boosted Trees, and Support Vector Machine. The Confusion Matrix assessed prediction accuracy. The DM procedure aimed to create predictions using a predictive model and characterize behaviors using a descriptive model. Predictive models used known outcomes, while descriptive models used identified patterns in data to guide decision-making.

Statistical techniques like logistic regression and time series can be used when analyzing the reasons for success or failure [26]. However, when forecasting is the primary goal, methods like neural networks [27], support vector machines [28], decision trees [29], and random forests [30] are more effective and produce more accurate results. Statistical methods are employed to create models that accurately predict output values, while supervised optimization issues enable machine learning techniques to automatically match input data with target values. The confusion matrix indicates model effectiveness, but no classifier performs well for prediction outcomes. Therefore, it's crucial to identify the most effective classifiers for the studied data. [31].

Figure 2: The flowchart for operationalization of the Predictive Analytics – AA Process

Web Design and Implementation

A synthetic dataset and a reproduction of the Higher Education Authority's database structure is created. The Authority data is utilized as a testbed for the framework's application. For storing data in the form of tables, MySQL is used. To publish data in JavaScript Object Notation (JSON) format, MySQL Representational State Transfer (REST) Application Programming Interface (API) data services are employed. A web interface for the integrated framework is created using the PHP programming language. SQL queries are employed to store and retrieve data. The proposed integrated framework is put into practice using the processes listed below:

1. Create a dataset using the data source, first.
2. Perform a dataset pre-processing.
3. Data conversion to a MySQL database.
4. Set up a RESTful API responsible for extracting processed data
5. Produce information in JSON format.
6. Create data extraction services for the integrated framework.
7. Define the information needs based on the accreditation process criteria, for this study the categories considered were staff academic alignment, academic staff course workload and academic staff moonlighting.
8. Present documentation in accordance with the requirements for the applicable accreditation.

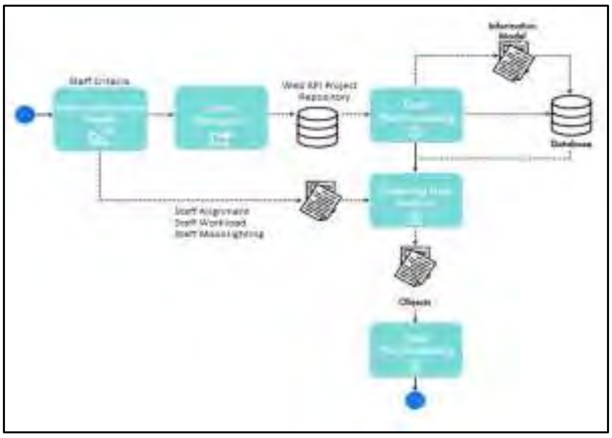

Figure 3: The flowchart for implementation of web design

C. Interpretation/Application

The experimental phase used Rapid Miner Machine Learning, a user-friendly data mining tool suitable for both experienced and novice data scientists. Data analysis was done by stacking widgets into workflows, each with specific activities like data retrieval, pre-processing, visualization, modeling, or evaluation. Comprehensive data analysis charts were created by merging multiple elements in a workflow, as shown in Figure 2.

Staff Academic Alignment

The standard checks for staff alignment of the assigned academic staff to their assigned courses based on their qualifications from a recognized Higher Education Institution and their specialization, in line with the International Standard Classification of Education (ISCED) framework. The ISCED is a framework for assembling, compiling and analysing cross-nationally comparable statistics on education [32].

Course workload

The Higher Education Authority analyzes course workload based on prerequisites for teaching complete courses, determining required contact hours based on trackable workload. Full courses require a minimum of 10 contact hours and a maximum of 12 hours per week. The model uses parameters like good, moderately high, or very high

Academic Staff Moonlighting

The study examines staff moonlighting by analyzing academic staff's bio information, workloads, and matching them with higher education institutions and learning programs, comparing matches based on defined information. According to Amini-Philips [33], [34], many professors experience illness and burnout as a result of extra work or side jobs. Moonlighting in teaching can lead to stress, decreased effectiveness of instruction, and increased preoccupation among lecturers [34], [35]. Academics who work long hours at a second job are more likely to perform poorly in their first teaching position. According to Hobbs and Stutz [34], [36], academic staff believe moonlighting negatively impacts instruction quality; this model helps accrediting process evaluators understand teaching job numbers.

IV.RESULTS

The dataset for this study was extracted from MySQL Database using PL/SQL [37]. The extracted raw data consisted of 1814 observations and 18 features [37]. In order to investigate the raw data and extract valuable insights from the dataset, we used a variety of EDA techniques. We deleted the category characteristics and reduced the feature list to 9 by using several Python functions, while also taking into mind the crucial features required for clustering.

A. Model Evaluation

The model provided an average of 70% accuracy in terms of evaluation of the provided information needs against the required accreditation criteria, showing that the predictive decision could be utilized to support the decision of the evaluation of the learning programme. Further, performance of model was evaluated with General Linear Model, Logistic Regression, Fast Large Margin, Deep Learning, Decision Tree, Random Forests, Gradient Boosted Trees and Support Vector Machine, confusion matrix and area under roc curve (AUC) metrics. Table 2 shows the model values.

Table 2 – Model Values

Model	Accuracy	Classification Error	AUC	Precision	Recall	F-Measure	Sensitivity	Specificity
Generalized Linear Model	68%	32%	0.759	77%	39%	51%	39%	91%
Logistic Regression	56%	44%	0.43		0%		0%	100%
Fast Large Margin	70%	30%	0.817	89.30%	38%	53%	38%	97%
Deep Learning	79%	21%	0.905	90%	60%	72%	60%	95%
Decision Tree	56%	44%	0.5		0%		0%	100%
Random Forest	95%	4.60%	0.965	90%	100%	95%	100%	92%
Gradient Boosted Trees	95%	4.60%	0.961	90%	100%	95%	100%	92%
Support Vector Machine	56%	44%	0.5		0%		0%	100%

B. Confusion Matrix

The confusion matrix displays the dataset's current state and the number of accurate and inaccurate model predictions. Tables 3 to 5 show models with over 70% accuracy. The ratio of correctly categorized examples to wrongly classified instances measures the model's performance. Columns reflect the model's estimation, while rows show actual sample counts in the test set. In the instance of Yes, the learning programme satisfied the criteria required for the provided information needs: Staff Alignment, Course workload and Moonlighting.

Table 3 – Deep Learning

	true no	true yes	class precision
pred. no	271	92	74.66%
pred. yes	15	139	90.26%
class recall	94.76%	60.17%	

Table 4 – Random Forest

	true no	true yes	class precision
pred. no	263	0	100.00%
pred. yes	24	232	90.62%
class recall	91.64%	100.00%	

Table 5 – Gradient Boosted Tree

	true no	true yes	class precision
pred. no	263	0	100.00%
pred. yes	24	232	90.62%
class recall	91.64%	100.00%	

C. ROC Curve

The ROC curve was utilized to assess the model's performance at different classification levels, plotting the true positive rate or recall against the false positive rate, thereby evaluating its effectiveness. The ROC curve that our model produced is displayed below: (Fig. 4)

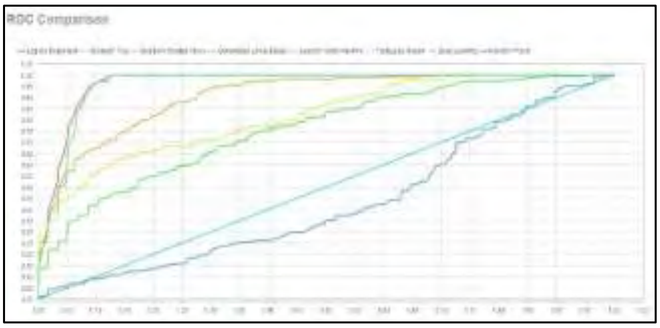

Figure 4: ROC Comparison

D. *Web Implementation Results*

Figure 6 shows the web implementation results for staff alignment data, allowing visualization of academic staff thematic areas, qualifications, specializations, and their appropriateness for courses, guiding evaluators and submitters on the appropriateness of academic staff.

Figure 5: Interface of Result – Academic Staff Alignment

V. DISCUSSION AND CONCLUSION

The research proposes a paradigm for knowledge discovery in educational data in higher education using data mining and machine learning. It analyzes data to determine if an academic learning program meets accreditation requirements from the Higher Education Authority. Machine learning algorithms like General Linear Model, Logistic Regression, Fast Large Margin, Deep Learning, Decision Tree, Random Forests, Gradient Boosted Trees, and Support Vector Machine are compared for predicting academic staff appropriateness and adequacy, considering alignment, course workload, and moonlighting. Further, this paper suggests that qualifications, specialization areas, course allocations, workloads, and side jobs are crucial predictors for academic personnel's suitability in the accreditation process at the Higher Education Authority. In light of this, the researcher suggests that future studies take into account the additional higher education institutions that the Higher Education Authority currently oversees as a result of the Amendment to the Higher Education Act No. 4. of 2013. Further, the methods can be developed for all the other accreditation criterion such as Introduction, Rationale, Teaching and Learning Plan, Curriculum, Internal Quality Assurance, Financial Resources and Regulations.

VI. ACKNOWLEDGEMENT

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