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Towards an Efficient Machine Learning Algorithm for a Graduate Study Elective Course Recommendation System

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***Abstract*— The choice Master's students have to make regarding elective subject selection in a chosen specialization is really decisive. A wrong decision may affect their personal and academic goals and may impact negatively on their future professional direction. Making bad choices on the elective subjects to offer at this stage may lead to loss of interest by the student, which can result to dropping out of the higher degree program. It is therefore important that students are given support so as to make the right choices regarding elective courses in a chosen specialization, using decision support systems. There are records of successful use of recommender systems to suggest items to users in several domains, like education, e-commerce, entertainment domains, and the like. In this work, 5 supervised machine learning algorithms are evaluated to determine the most efficient for the training and prediction on elective courses to be offered by a Master's Degree student based on the student's background knowledge of undergraduate courses, and on the academic record of previous Master's students. This research employed an experimental approach, and a Python software application is modeled with the Object-Oriented Analysis and Design (OOAD) using the standards notations and techniques of the Unified Modelling Language (UML) to build the recommender system. The result from the evaluation of the five machine learning models shows that the Naïve Bayes and Decision Tree algorithms have equal accuracy value of 99.409%, which is the highest and an equal F1 Score of 0.918, which is equally the highest. Decision tree was selected to be the classifier model for the recommender system.**

Keywords— Educational Data mining, Recommender system, machine learning algorithms

I. Introduction

Apart from core courses, most postgraduate programs in higher institutions give room for students to select elective courses they may wish to offer based on their chosen specialization. Core courses are mandatory courses (also known as Major courses) for all students, regardless of specialization, while elective courses are optional courses (specialized courses) that when added to the core courses, make up the total unit needed to complete a degree. Since the scores of elective courses are added to make up a student's final result. Selecting the right elective course(s) should also be important. However, most students find it difficult deciding on the elective courses to offer in their chosen area. For instance, a postgraduate student might find himself in a new environment different from his undergraduates', where it might be difficult to find someone to consult for counsel on elective courses to choose from. There is also the fear of not being able to deduce his level of competence for the intended course(s) from discussions with past students, who might not readily be available, since it is a postgraduate program. Many other challenges could face such a student, such as the lack of a guidance and counseling unit at that level, or the inability of a supervisor to offer a useful advice since he may not have known the student's competences. In such scenarios, the student tends to go with the cohort choice. This results to a gap in the required skills set for the chosen elective course and the student's actual skills which may lead to loss of interest by the student, hence resulting to a degraded academic performance which will be encountered by not only the student but the institution at large. Offering the right set of elective courses will not only sustain a student's interest, it will also provide a guide for the area of specialization and promote academic excellence.

Universities generate huge amount of data relating to all students' academic history. These data can be used to create meaningful research that will better the university and the economy at large. Data mining can be used in such regard. Data mining is the extraction or mining of useful data from huge database [1]. It is the process of recognizing patterns in huge datasets. There are several data mining techniques, some approaches like content-based, collaborative filtering and their hybrid have been commonly used to build recommender systems.

Since the question that masters' students ask at the end of the day is "Could this be the right elective course for me to offer?", a recommendation system is deployed in this work to help suggest elective subject(s) to the student based on his/her background knowledge of undergraduate courses and academic records of previous masters' students. Decision tree algorithm is chosen to be the most efficient algorithm after been examined alongside 4 other machine learning algorithms using some evaluation metrics and deployed in this work to train the system with the dataset gotten from previous masters' students' results. The rest of the sections are as follows: Section 2 discusses machine learning concepts

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while Section 3 presents details of the research work. Section 4 shows and compares the results of different machine learning algorithms employed in this research.

II. REVIEW OF RELATED LITERATURE

Education data mining recently has been an area of interest by most academic researchers. Various ideas and works are created and published to facilitate the teaching and learning process. In the past, education data mining has been used mainly for the understanding of students' behavior and predicting students' performance. Presently, researchers are diving into using educational data mining for course recommendation. Authors in [2] believe that educational datasets have so many hidden knowledge for the prediction of students' performance in courses which will in turn help in achieving higher quality of education in institutions and to extract this information, data mining techniques must be used. Their study was conducted using 50 students in VBS Purvanchal University, Jaunpur datasets. In order to predict the performance of students at the end of the semester, information used to indicate performance like Attendance lists, Assignment marks, Seminar and Class test were collected from the student's previous database of the school. Decision tree algorithm (Iterative Dichotomies 3 (ID3)) was used for classification to extract knowledge that express the performance of students in end of semester examination. This they believe will help at an early stage in recognizing dropouts and the students that need extra attention in order to assist them in their educational process to obtain a better result.

Hans in [3] developed and evaluated a recommender system by name Classmate for selection of course. It uses hybrid of both collaborative filtering (CF) and content-based filtering. To strengthen the accuracy of the results, the social graph of the user and the degree subject chosen are used as signals in the collaborative filtering algorithm. Unfortunately, one of the goals, that is, to creating a recommender system fit enough (fast, scalable, accurate) to be used in a production environment was not actualized fully because its correlation calculations is done off-line and takes every 24 hours to run. This means that every rating made by student waits for 24 hours before reflecting in the recommendation.

Park, et.al. in [4] did a review on 210 articles related to recommender systems published between years 2001-2010. The work used features like year of publication, application fields (images, music, books, images, documents, TV programs shopping and others), journals that these articles appeared and techniques in data mining to classify these articles so as to observe the research trends. This work helps to give insight to the future of recommender systems.

According to [5], Educational Data Mining (EDM) put in techniques coming from machine learning, statistics and data mining to examine data collected during tests learning theories, teaching, and learning and informs decision-making in educational practice. They believe that EDM bring inter-disciplines from other fields like learning scientists, researchers, psychometricians and computer science together. These researchers analyzed EDM, showing some applications, tools and future insights of EDM. In addition, they see recommender systems as one of the best ways to present results, recommendations, explanations or other information to a non-expert user in data mining. Furthermore, methods of EDM such as prediction, clustering, knowledge tracing, discovery with models, Social Network Analysis (SNA), outlier detection were elaborated.

Researchers in [6] proposed a web-based implementation called CareerMaker for elective course recommendation. CareerMaker suggests a list of preference courses based on the requirements of the job market. It provides suggestions of elective courses based on everyone's employment demand. It considers three major steps in order to achieve this. Firstly, interviewing several workers from workplaces to get the core values most appreciated for each workplace. Secondly, getting the matrix of the core values of the job categories, and finally the matrix of the courses and core values were the steps taken. It uses content-based filtering and collaborative filtering to compile the recommendation course list and its architecture is centered on rule base. Unfortunately, CareerMaker prediction is based on the present and most popular career market demands and does not consider the future.

Fabio in [7] designed a Masters Courses recommendation system that aims at predicting marks of students' Masters Courses, so as to be able to suggest the Masters courses that are more suitable to the students' capabilities. Here, the student inputs his bachelors result in order to get recommendation. Singular Value Decomposition (SVD) was put into context to know how it is commonly used for recommending items. The recommendation problem was grouped into two: the prediction of marks and the recommendations creation. Furthermore, the use of Mean Absolute Error (MAE), a prediction accuracy metrics in applied statistics is used to check how the average of the absolute contrast between the prediction of the course mark and the obtained real mark for all the Masters courses in the test set corresponds. The research proves that the educational paradigm can be combined with User-Based Collaborative Filtering and Singular Value Decomposition in order to investigate historical student data and be able to describe and predict students' Masters Courses marks.

Authors in [8] present a work on different techniques in EDM showing how all the stakeholders (Students, Professors, Administration, Supporting administration) could use it for their benefits in the educational system. Data Mining (DM) techniques like Decision Trees and Regression were used to execute the prediction of academic performance of students and were found to be effective. Also, these DM techniques were used to predict academic failure as well. Clustering was used to successfully group students into clusters according to their academic weaknesses and strengths.

Researchers in [9] present a paper on a collaborative recommender system which recommends elective courses to students on the basis of courses taken by other similar students. Patterns between courses are discovered by an

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underlying technique known as association rule mining algorithm. The work proposes the combination of Collaborative Filtering recommender method with Content-based or knowledge-based approach in order to overcome the incompleteness of pure recommender systems. Grewal and Kaur in [10] designed a framework of intelligent student recommender system for course selection by students based on their choice of job interest and their marks. It considers issues relating to the problem of course selection for students in all streams and provides an effective solution to it. Relationship and structures within data is considered using clustering technique. The framework uses techniques like Feed-Forward back propagation probabilistic neural network and classification using Rough Set and Fuzzy Logic.

EDM has helped in the last few years in providing valuable solutions in making one or more choices among many available choices by focusing on logical relationships [14]. An elective course selection recommender system based on the previous year students' datasets and by using the Fuzzy logic system was proposed by [15]. Here, elective subject suggestion is predicted using the fuzzy logic by giving the approximation idea for the student and upon the defuzzification will give the accurate analysis towards the elective subjects to be taken by focusing on the recommendations so far. The work uses C4.5 algorithm to actualize the selection of the subject. Amjad [16] attempted to explore multiple factors theoretically presumed to influence the performance of students in institutions. The researcher tried to find a qualitative model which classifies and predicts best the performance of students' using related social factors, personal factors and their academic performances.

III. MATERIAL AND METHODS

This section describes the experiment, data collection, and processing. We also discuss how the algorithms were chosen and trained.

A. Dataset Description, Preparation and Usage

A dataset for over 250 graduate students, each from four areas of specialization (AOS) was used, as shown in fig. 1. Each AOS, having the records of students that offered several courses alongside two core courses in that specialization. The Areas of specialization used were Artificial intelligent (AI), Software Engineering (SE), System Engineering (SYE) and Computer Networks (CN).

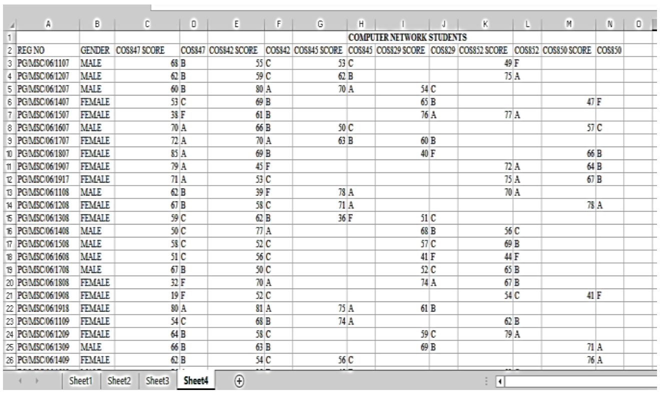

Fig. 1. *Screenshot of raw data for computer networks students*

a. Feature selection

Within the anonymous dataset, from each course title, 2 relevant features (Course score, and Course grade) were selected out of 4 features consisting of Reg no, Gender, Course score, and Course grade. Missing or incomplete data were removed in order to get a clean dataset. Next is to prepare the data in a usable format.

b. Data Categorization

The selected features were subjected to categorization. It was noticed that using course grades A, B, C & F as our classes (outcome) will result to having a large margin. Consider a student having grade of a in two or more courses in a specialization, ranking the highest scored course here will be difficult using grade. A course with a score of 90 should be considered first before a course with score of 78 despite both having the same grade range. Therefore, the process of data binning was applied to convert the course scores from continuous variables to discrete variables. Now, the binning of data is categorized as such, 0-5 (1), 6-10 (2), 11-15 (3), 16-20 (4), 21-25 (5), 26-30 (6), 31-35 (7), 36-40 (8), 41-45 (9), 46-50 (10), 51-55 (11), 56-60 (12), 61-65 (13), 66-70 (14),71-75 (15), 76-80 (16), 81-85 (17), 86-90 (18), 91-95 (19), 96-100 (20) [11,12]. This results in a third feature called "Grade bin". This grade bin feature will be derived from the course score of the dataset. With the presence of grade bin feature, the course grade becomes irrelevant in our classification. Furthermore, grade bin 1 is categorized in such a way that it falls under class 0, 2 - class 1, 3 - class 2 etc. down to 20 – (i.e. class 19). The feature containing the classes is named "Category" and this will serve as the target variable having 20 possible outcomes (class 0 – class 19). Therefore, the features used for the classification are "Course Score", "Grade Bin" and "Category". Table I shows a sample of how the data is represented:

TABLE I. SAMPLE OF DATA REPRESENTATION

Course Score	*Grade Bin*	*Category (Class)*
70	14	13
65	13	12
90	18	17
55	11	10
10	2	1
47	10	9
34	7	6
94	19	18
12	3	2
53	11	10
48	10	9

c. Training the system

The training set is used to train a model. It must have predictor variables (course score and grade bin) and a target variable (category) that has been pre-classified. The test set on the other hand is used to validate the model. When training a system, the system is fed with both the independent variable and the dependent variable but when testing a system, the system is only fed with the independent variable and it is left to determine the dependent (since it has been trained). After getting the data prepared, the dataset was split into 2 parts (80% training set and 20% test set). 80% of the prepared dataset was used to train the system and 20% was reserved to test the system.

d. How the system predicts elective courses

The process of predicting elective courses starts once a student finishes his test, the results of the answers are summed under their respective courses. The total results from each course are inputted separately in the "Course Score" feature, the "Grade Bin" feature is derived and the trained system predicts the Category. After the Categories of the test results from each course are predicted, the results are ranked in increasing order. The first two courses after being ranked are recommended to the student.

With the attempt to reduce bias to the barest minimal, a physical factor was still used in a situation where ranked results tallied with the first outcome to the third and we need just two courses to recommend. In this case, external factors were introduced to solve the problem. Each tallied course was gotten, then the number of previous students that offered that course was taken and divided by the mode of the students that were in the said score range to get a floating number. The smaller the number, the better for selection. The calculation is shown (1).

$$\text{Minimal preference} = \frac{Tnps}{ns} \qquad (1)$$

Where Tnps = Total number of previous students in a particular course, and ns=Number of students in a particular score range
Optimal_minimal_preference = sorted (minimal preference)

IV. EXPERIMENTS AND RESULTS

A. Classification Techniques used

When approaching a machine learning problem, there are numerous algorithms to choose from, as no one algorithm is best for all problems. The structure and size of the data is a strong determinant on which machine learning algorithm to choose, but the right algorithm to use still remains unclear until some trial and errors tests are made directly using some algorithm thoughtfully selected.

Five known classification models used in Machine learning were selected for this work namely:

- Decision Trees
- K-Nearest Neighbours
- Logistic Regression
- Linear Support Vector Machine
- Naïve Bayes

These algorithms are very popular and they helped in the prediction of our possible outcome. The same dataset was used to train these various algorithms and the algorithms were evaluated to know the best prediction model to be used for the work.

B. Evaluation measures used in the work

It is a good practice to test a system after being trained. This helps to know if that model's prediction is closer to the actual truth or not. The result of the system's test becomes the predicted outcome, while the dependent variable that was not fed to the system becomes the actual outcome. As earlier stated, 20% of the dataset was reserved to test the system, it will be fed to the already trained 6 models excluding the actual outcomes (Category). The results from each model (algorithm) will be subjected to the evaluations metrics below to check the most efficient/effective algorithm:

- Confusion Matrix (Error Matrix)

Confusion matrix is a tabular description of the performance of a supervised machine learning model on the testing set, where true values are known. The output of a confusion matrix is a matrix. In the matrix, each column represents instances in an actual class (actual outcome) while each row shows instances in a predicted class (predicted outcome). Confusion matrix can be used for classification problem where the classes of the output are two or more types. When there are 2 outcomes (classes), there will be 2 rows and 2 columns in the confusion matrix (see Table II), 3 outcomes will be 3 rows and 3 columns, 20 outcomes will be 20 rows and 20 columns, etc.

TABLE II. THE CONFUSION MATRIX FOR A TWO-CLASS (BINARY) CLASSIFICATION PROBLEM

Predicted Class			
		Class 1	***Class 0***
	Class 1	True Positive (TP)	False Negative (FN)
	Class 0	False Positive (FP)	True Negative (TN)

Important terms to note:

True Positives (TP): cases when YES was predicted and YES was also the actual output. When the classes in confusion matrix exceeds two, say three, four and above, the diagonal outputs in a confusion matrix is seen as the true positive. They tell how many times the algorithm classified the outcome correctly.

True Negatives (TN): cases when NO was predicted and NO was also the actual output. The total number of true negative for a certain class will be the sum of all columns and rows excluding that present class's column and row.

False Positives (FP): cases when YES was predicted and No was the actual output. The total number of false positive for a certain class is the sum of values in the corresponding column excluding the TP.

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False Negatives (FN): cases when NO was predicted and YES was the actual output. The total number of false negative for a certain class is the sum of values in the corresponding row excluding the TP.

Confusion matrix stands as the basis for other metrics here. To evaluate the quality of the classifications, four standard measures were used namely accuracy, precision, recall and F1 score.

- Accuracy

Accuracy can be calculated from the confusion matrix as the sum of correct classification (TP) divided by the total number of classifications. It is calculated as in (2).

$$Accuracy = \frac{No\ of\ correct\ predictions}{Total\ no\ of\ predictions\ made} \quad (2)$$

- Precision

It is calculated from the confusion matrix as the number of true positives divided by the result of adding the number of true positive and the number of false positives. The precision for a considered class can be calculated from the confusion matrix as in (3):

$$Precision\ (p) = \frac{TP}{(TP+FP)} \quad (3)$$

For multiple classes, the average precision is calculated as:

$$Average\ Precision = \frac{(P_1 + P_2 + P_3 + \cdots + P_n)}{n}$$

Where n = number of classes

- Recall (Sensitivity)

Recall also known as Sensitivity is defined as the number of true positives over the number of true positives plus the number of false negatives. The recall for a considered class can be calculated from the confusion matrix as in (4):

$$Recall\ (R) = \frac{TP}{(TP+FN)} \quad (4)$$

For different data models used, the recall value ranges from a scale of 0 to 1

For multiple classes, the average recall is calculated as:

$$Average\ Recall = \frac{(R_1 + R_2 + R_3 + \cdots + R_n)}{n}$$

Where n = number of classes

- F1 Score

For binary classification in statistical analysis, F1 score, also known as F measure is a measure of the test accuracy. It is calculated by considering both precision and recall of the test as given in the following equation (5):

$$F1\ Score = (2 * \frac{(Precision * Recall)}{(Recall + Precision)}) \quad (5)$$

For different data models used, the F1 score value ranges from a scale of 0 to 1 [11], [12],[13].

This work has 20 possible outcomes (classes) ranging from 0 to 19. Therefore, there will be 20 rows and 20 columns. Figs 2-4 shows 3 of the 6 confusion matrix notations for the six classification models considered.

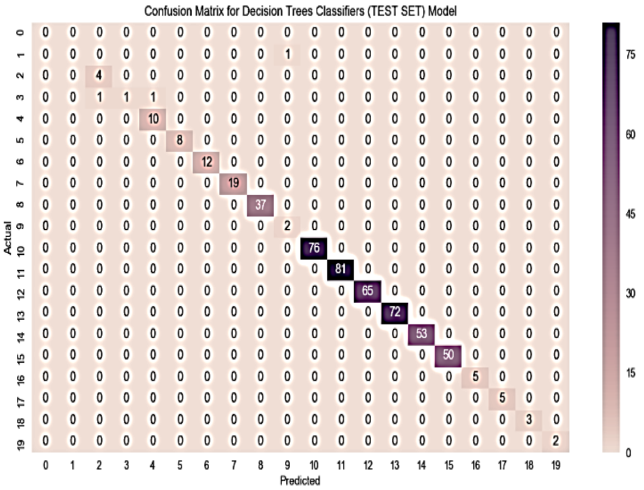

Fig. 2. *Confusion matrix for decision tree classifier (test set) model*

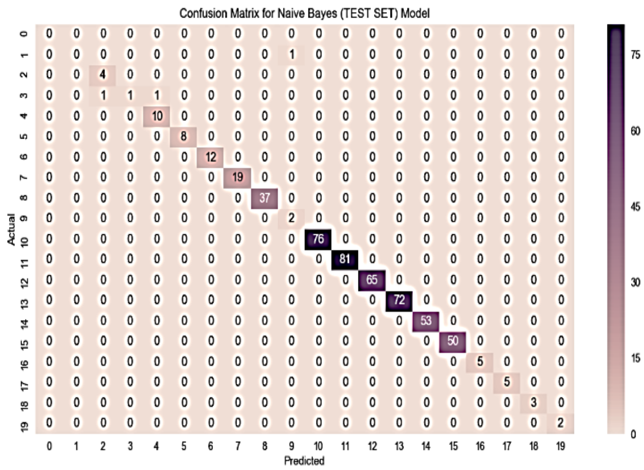

Fig. 3. *Confusion matrix for naïve bayes (test set) model*

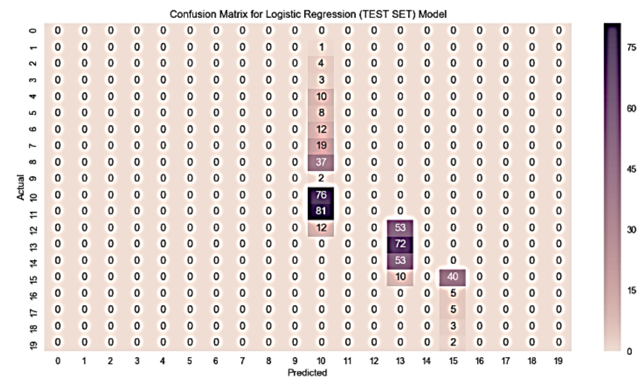

Fig. 4. *Confusion matrix for logistic regression (test set) model*

C. Results

This section presents the results of subjecting the six selected classification models to evaluation using the selected metrics. Since this work has 20 possible outcomes, the evaluation measure calculations were done using accuracy, precision, recall and F1 Score functions from Scikit-learn library (Sklearn library). Scikit-learn is a library in machine learning for python programming language with various features such as regression, clustering, classification algorithms, preprocessing, model selection etc. From our table we have Decision Tree and Naïve Bayes with the highest Accuracy values of 99.409% and F1 Scores of 0.918 each. F1 score was used to model performance here since it quantifies the performance of an imperfect data. For a perfect data, the F1 score will be 1. The higher the F1 Score of a classification model, the better the prediction. F1 score also has properties of model precision and Recall.

Decision Tree was chosen as the preferred model for this work with F1 score of 0.918 which is close to 1 after the use of some evaluation measures to analyze the different classification models used in this work as seen in table III, thereby making it efficient and reliable [13].

TABLE III: MODEL PERFORMANCE BASED ON FOUR EVALUATION METRICS

Evaluation Measure	***Linear SVM***	***Decision Trees***	***Logistic Regression***	***Naïve Bayes***	***K-Nearest Neighbours***
Accuracy	93.307 %	99.409 %	37.008%	99.409 %	99.213%
Average Precision	0.694	0.919	0.074	0.919	0.911
Average Recall	0.741	0.917	0.147	0.917	0.906
F1 Score	0.7	0.918	0.093	0.918	0.896

Fig. 5 shows a screen shot of a sample test result for a prospective student of Artificial Intelligence (AI), who is using the system to determine the elective courses to choose from under the AI specialization.

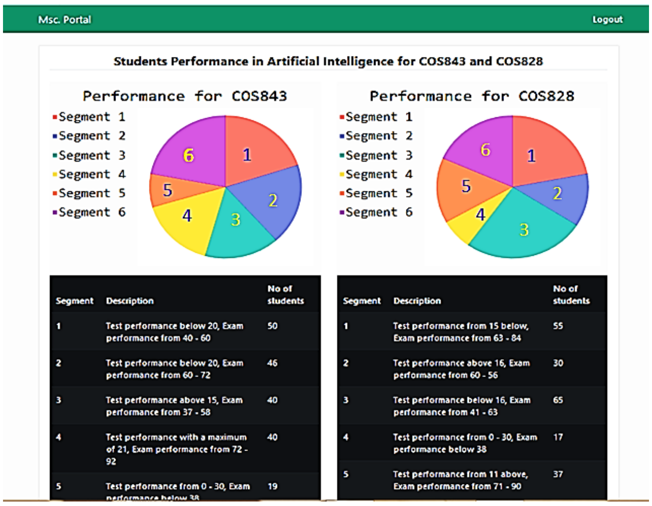

Fig. 5. *Screenshot showing the performance of previous students on core courses in Artificial intelligence*

Fig. 6, shows two elective courses recommended to the student by the recommender system. The suggested course codes are COS 838, and COS 836, which are Neural networks and Machine learning, respectively.

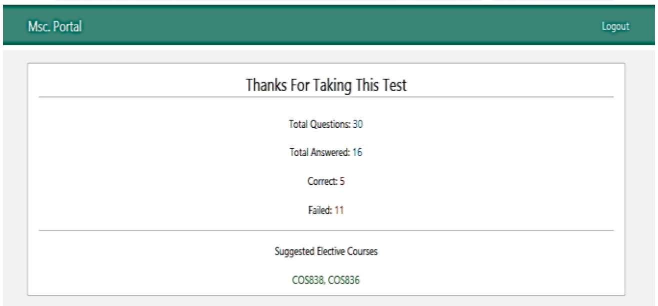

Fig. 6. *Screenshot showing two courses recommended for a student after taking the test*

V. DISCUSSION

In this work, efforts were put so as to get an efficient and effective algorithm for the prediction of elective course(s) for a Computer Science student. A comparative analysis of five classification algorithms namely Decision trees, K-Nearest Neighbors, Naïve Bayes, Linear Support Vector Machine and Logistic regression was conducted in this study.

The result shows that Decision Tree and Naïve Bayes has equal accuracy of 99.41% which is the highest and equal F1 Score of 0.92 which is equally the highest. Decision tree was selected as the classification model for predicting the elective courses based on the test results obtained by the student seeking for recommendation. Past students' records were used to train the model.

The implication of this work is that, with supervised machine learning it is possible to predict the performance of a prospective student in a course he/she has not yet enrolled for, based on the student's historical data. Such a system is a personalized decision support system that a prospective student can use to gain advise on the area of specialization for his/her intended graduate studies. It is also important to note that all the algorithms used for training the model performed very well with accuracy values above 90%, except Logistic regression.

We can use any of the other algorithms apart from logistic regression which is not suitable for continuous variables as used in this work. Logistic regression is better suited to categorical variables. And logistic regression is a probabilistic model based on two outcomes. For example, if we want to predict whether a student will pass or fail, then logistic regression would have been a better choice. So, based on the above, logistic regression is completely out of consideration for a classification problem as this.

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