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Predicting the Enrollment and Dropout of Students in the Post-Graduation Degree using Machine Learning Classifier

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Abstract*: *Nowadays, In Bangladesh, the dropout rate at post-graduation level or incompletion of the post-graduation degree is considered as a serious problem in the education sector. This work can be used to support for identifying the specific individuals as well as the institutional factors which may next lead to the enrollment or drop out at the post-graduation degree. The real dataset is used to accomplish this work. Here, seven classification algorithms namely Naïve Bayes, Multilayer Perceptron, Logistic, Locally Weighted Learning (LWL), Random Forest, Random Tree, and Part are applied in this context. A confusion matrix is calculated for each classification model. Then, we computed all the seven performance evaluation metrics (accuracy, sensitivity, precision, specificity, F1 score, FPR, and FNR). Each classifier's performances are analyzed and measured from the computed performance evaluation metrics. Naïve Bayes, LWL, and Part classifier perform better than all other working classifiers attaining 86.36% accuracy and on the contrary, Random Tree classifier performs worst achieving 74.24% accuracy. After further analyzing of the result based on performance evaluation metrics, it is observed that LWL classifier performed best in this context among all the classifiers.

Keywords*: *Machine Learning, Data Mining, Classification, Post-Graduation, Enrollment, Dropout.

I. INTRODUCTION

In recent times, Machine learning technique has achieved more popularity. Machine learning technique assists researchers to make a more intelligent system, which can execute different types of assignments autonomously without extremely intercession of human, by training them with a valid dataset. The main purpose of the machine learning technique is to generalize beyond the samples in the training set. So it is reasonable to predict something with a great accuracy level from the training set [1]. Several techniques of machine learning have been stationed in various field of use. Performance of certain algorithms depends on the problem domain which means the working ability level of the machine learning algorithm is problem specific. So it is crucial to compare the various off-the-shelf machine learning algorithms' performances for this domain.

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Bangladesh has a total of 45 public universities [2] all over the country. Most of the public universities have the post-graduation program. Nowadays some of the students couldn't continue their post-graduation after completion of their graduation. Now, it is an alarming issue for our development. There are lots of academic and personal factors which is directly or indirectly lead to invoking for not to complete the individual's post-graduation degree. In this work, we have tried to find out specific individuals as well as an institutional factor affecting the completion and dropout of the post-graduation program.

Here seven machine learning classification algorithms are used in this context to find out the actual causes of discontinuity of post-graduation degree. We have compared their performance based on the seven well-known performance metrics. Then we have shown the best classification algorithms among all the working machine learning models in this context

The foundation of this paper is presented as follows: Section II outlines the relevant existing works designated as Literature Review. Research methodology and also the applied techniques to accomplish this work are described in Section III. Section IV exhibits the test results and analyze the obtained results. Subsequently, Section V concludes this work with mentioning future work.

II. LITERATURE REVIEW

Three popular machine learning approaches namely SVM, feedforward neural networks, and probabilistic ensemble simplified fuzzy ARTMAP were applied by Lykourentzou et al. [5] for predicting the dropout in e-learning courses. The methods were examined by several model evaluation metrics. Its obtained outcomes were observed to be better enough than those stated in the related literature.

Márquez-Vera et al. [6] proposed to employ data mining methods to predict dropout and failure. They used real data of 670 middle-school students and apply white-box classification methods, namely decision trees, and induction rules. Experiments try to develop their predicting accuracy to determine which students might drop out or fail. For this, initial, utilizing whole attributes; then, deciding the most suitable attributes; and lastly, doing data rebalancing and utilizing cost-sensitive classification. The obtained consequences were compared and the best results with the model were exhibited.

A machine learning framework was proposed by Kloft et al. [7] for the dropout prediction in Massive Open Online Courses.

Their proposed approach worked on click-stream data. Amidst other features, the algorithm considers into account the weekly history student data and consequently is capable to notify the diversity in the behavior of student over the period. In the later phases of a course, the approach is capable significantly for the dropout prediction than the baseline methods.

In [8], academic performance and students' characteristics were selected as input attributions based on the analysis of related literature and developed prediction models using Decision Tree, Artificial Neural Network, and Bayesian Networks. In the point of the prediction models training and testing, a comprehensive sample of 62,375 students was used and confusion matrix was used to present the results of each model and was investigated by determining the several performance evaluation metrics. The outcomes recommended that all working models were effective for this context, but Decision Tree performed better comparatively.

A systematic literature review was presented by Alban et al. [9] considering the data mining aspects for predicting the dropout at university. They recognized 1,681 elemental related studies and selected 67 documents according to the established inclusion and exclusion criteria and also recognizing five major dimensions. In this study, an inventory of 112 factors was made that had an impact on the prediction and arranged into five dimensions: academic, personal, social, economic, and institutional. The personal dimension as the most usually studied which considered factors such as gender, age, and ethnicity and also identified ten pre-processing methods, the most popularly used being normalization, and discretization. Principle component analysis and descriptive statistics were most referenced for factor selection among the ten techniques. Additionally, four-teen techniques were recognized for the prediction of dropout. But they could not distinguish one technique that is surely superior and it is observed that accuracy of the prediction is dependent mainly on the context, data and technique features.

In [10], a threshold-based strategy was introduced to recognize dropouts and observed that the proposed approach outperforms than the existing approaches. The value of the threshold can be calculated from the extracted features. Not a single classifier is required for classifying the new pattern if the value of the threshold is computed. The value of the threshold of only the new pattern has to be determined and then compared with the earlier calculated value of the threshold and could be classified. If the value of the threshold is smaller than the calculated threshold value, then it can be said that there is a possibility of drop out. Their work was limited to employing the method for original datasets and for the datasets of after identifying outliers.

Slim et al. [15] identified factors that affect the possibility of enrolling and used machine learning approaches to analyze statistically the enrollment predictability of the factors. They mainly used support vector machines, logistic regression, and semi-supervised probability methods and validated the methods using real data. The results of their work showed that a little set of factors linked to student and college characteristics are extremely correlated to the decision of enrollment of applicant. The outcome was supported by the high prediction accuracy of their proposed methods.

A study on predicting the dropout in Massive Open Online Course (MOOCs) was presented by Liang et al. [16] and they collected thirty-nine courses data from XuetangX platform, which is mainly based on the open-source Edx platform. Here, using the supervised classification strategy, 89% accuracy was achieved with the gradient boosting decision tree model.

A methodology including a particular classification algorithm was proposed by Márquez-Vera et al. [17] to create an intelligible dropout prediction model of the student. They utilized data assembled from 419 high schools students in Mexico. They performed various experiments for dropout prediction at various steps of the course to decide the most reliable dropout pointers and to compare their suggested approach with some of the classical and also imbalanced familiar classification algorithms. The obtained result of this work showed that their algorithm could predict the dropout of the student within the initial 4 to 6 weeks of the course and reliable fairly to be employed in an initial warning system.

Koutina et al. [18] investigated the most competent machine learning approach for predicting the ultimate grade of postgraduate students of Informatics of Ionian University. To accomplish this work, 5 courses (academic) were selected and each constituting a specific dataset. Here, 6 popular classification algorithms were studied with. 1-NN and Naïve Bayes performed the most excellent results, which are very satisfying comparatively.

Lestari et al. [19] performed a comparison between the two data mining classification methods. They implemented the two algorithms namely Naïve Bayes and C4.5 on enrolment (non-written) system. This work presented that the Naïve Bayes classification accuracy is greater than another algorithm.

Anderson et al. [20] applied a set of machine learning models to predict six-year graduation for university undergraduate students using Decision Trees, Logistic Regression, Stochastic Gradient Descent binary classifiers, and Linear Support Vector Machines. They used a data set of over 14,000 students from six fall cohorts, holding 104 features. The model achieved high performance, and identify GPA and completed credit hours as the most significant predictors.

III. METHODOLOGY

The methodology section is organized by the four subsections namely, A) Dataset Description, B) Classifier Description, C) Confusion Matrix and Classifier Evaluation Metrics, D) Implementation Procedure. The details of these four subsections are presented below.

A. Dataset Description

The real dataset is used here to accomplish this research. In this research, total six types of attributes of students such as graduation year, the gender of a student, marital status of a student, job status of a student, the result of a student at graduation level, and post-graduation completion status of a student are used here to carry out this work. Here, graduation year, the gender of a student, marital status of a student, job status of a student, and the result of a student at graduation level are considered into the explanatory variable and post-graduation completion status is response variable. All the data used in this research are collected from a renowned public university of Bangladesh and a survey on the students (individual for whom data is collected).

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We are mainly working on the last six years (graduation passing year from 2012 to 2017) student data of a well-known department of a reputed public university of Bangladesh. Here total 70% data are used for training the classifier and remainder 30% are used for testing the performance or correctness of the classifier.

B. Classifier Description

We have used **Naïve Bayes** classifier here. This classifier is an implementation of Bayesian classification methods. It makes use of Bayes' theorem for predicting class and measures the class-conditional probability by considering that the attributes are conditionally independent, given the class label [4]. This classifier can solve binary and also multiclass classification problems with the independence assumptions between predictors. Our work is mainly a binary classification problem.

A multilayer perceptron is a feedforward neural network consisting of three types of layers. It has one or more hidden layers apart from one input and one output layer. In the context of the practical application, a multilayer perceptron is considered more useful than single-layer perceptron. A single layer perceptron can learn only linear functions whereas a multilayer perceptron can learn also nonlinear functions. The backpropagation algorithm is used to learn the multilayer perceptron [12].

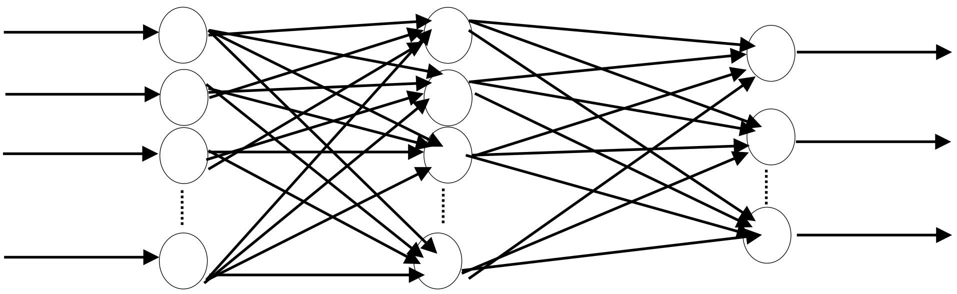

Fig. 1. A Multilayer Perceptron with one hidden layer.

We have applied a classifier named as **logistic regression** [11]. It is a statistical strategy for examining a data set with one or more independent variables that decide a result. A dichotomous variable is used here to measure the outcome (only two possible outcomes). The idea of this classifier is to find the best fitting model to illustrate the relationship between the outcome variable and predictor variables with the support of the logistic function. If p is the probability of the presence of the characteristic of interest then the probability of the absence of the characteristic of interest is 1-p. Then the logit transformation is defined as the logged odds:

$$odds = \frac{p}{1-p} \qquad (1)$$

and

$$logit(p) = \ln\frac{p}{1-p}\ ; \quad where\ 0 < p < 1 \qquad (2)$$

LWL is a Lazy classifier. It is an algorithm for locally weighted learning. It assigns weights through an instance-based method and establishes a classifier from the weighted instances [14].

Random forest is a part of ensemble methods particularly designed for the classifier i.e, decision tree. Predictions performed by multiple trees (decision trees) are mainly combined by the random forest classifier, where each decision tree is created based on the values of an independent dataset of random vectors [3, 4].

The random tree is a classifier used here. The random tree is a tree-based supervised classifier. It is a class for building a tree that considers k chosen attributes (randomly) at each node. Random tree performs no pruning. Random Forest classifier builds forests by bagging ensembles of random trees [13, 14].

The part is a rule-based classifier. The part classifier obtains rules from partial decision trees made utilizing classifier J4.8 [14]. Because of this, the classifier J4.8 and part can give the same result for a particular dataset.

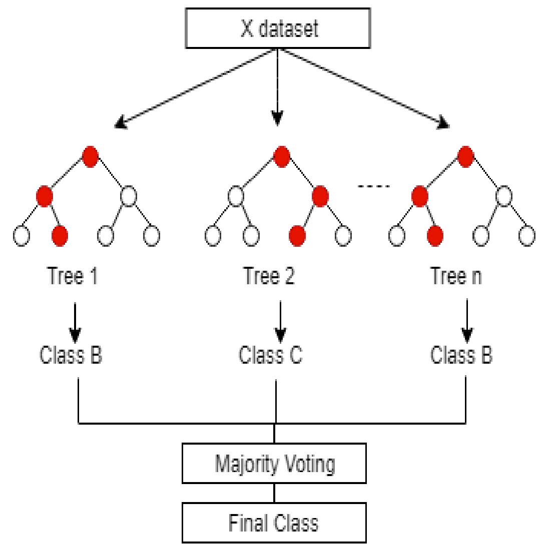

Fig. 2. Working procedure of Random Forest classifier.

C. Confusion Matrix and Classifier Evaluation Metrics

The confusion matrix is a form to show the number of instances predicted correctly or predicted incorrectly by a classification algorithm [4]. This matrix can be employed to assess the quality of a classifier. Here, we are working with the two-class problem. In the case of the two-class problem, it exhibits the true positives, true negatives, false positives, and false negatives. In this work, the following terms denote:

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True Positives (TP): The situation when the model predicts the enrollment of a student in the post-graduation degree and also the actual output indicates the enrollment of a student in the post-graduation degree.
True Negatives (TN): The situation when the model predicts the dropout of a student in the post-graduation degree and also the actual output indicates the dropout of a student in the post-graduation degree.
False Positives (FP): The situation when the model predicts the enrollment of a student in the post-graduation degree but the actual output indicates the dropout of a student in the post-graduation degree.
False Negatives (FN): The situation when the model predicts the dropout of a student from the post-graduation degree but the actual output indicates the enrollment of a student in the post-graduation degree.
Accuracy, Sensitivity, Specificity, and Precision are used to measure the predictive ability of a class classifier [3]. We can calculate the performance evaluation metrics such as accuracy, sensitivity, specificity, precision, F1 score, False Positive Rate (FPR), and False Negative Rate (FNR)) of the classifier with the help of confusion matrix. All of these evaluation metrics can be calculated by the following formula (From equation 3 to 9). Here all of the evaluation metrics are presented by the percentage.

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+FP+TN} \times 100\%. \tag{3}$$

$$\text{Sensitivity or Recall} = \frac{TP}{TP+FN} \times 100\% \tag{4}$$

$$\text{Specificity} = \frac{TN}{FP+TN} \times 100\% \tag{5}$$

$$\text{Precision} = \frac{TP}{TP+FP} \times 100\% \tag{6}$$

$$FPR = \frac{FP}{FP+TN} \times 100\% \tag{7}$$

$$FNR = \frac{FN}{FN+TP} \times 100\% \tag{8}$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \times 100\% \tag{9}$$

D. Implementation Procedure

Implementation procedure and comparing the approach of this work is described in the following in FIGURE 1. First, we have collected the student data which consists of six attributes. Then we have stored the collected data and converted the data into the arff (Attribute-Relation File Format) format. Then we have applied all the seven classifiers i.e., Naïve Bayes, Multilayer Perceptron, Logistic Regression, LWL, Random Forest, Random Tree, and Part individually on the dataset and obtained the confusion matrix with TP, TN, FP, and FN. Then we have calculated the results of the above-mentioned evaluation metrics with the help of equation 3 to equation 9. After this, we have compared the obtained result in terms of seven evaluation metrics. Last, we have analyzed the obtained experimental result to make our decision for finding out the most competent classifier among all the applied classifier (seven classifiers).

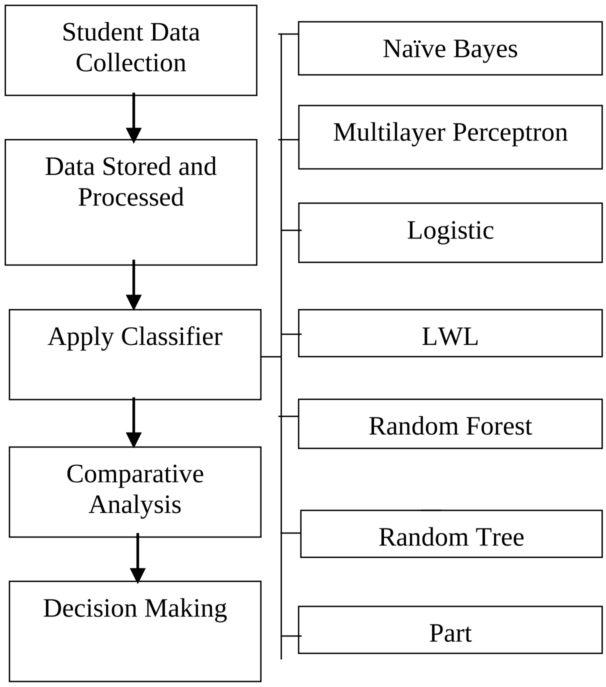

Fig. 3. Implementation and comparing approach for the classifiers to predict the enrollment and dropout in the post-graduation degree.

IV. RESULT AND DISCUSSION

All the experimental obtained results for this work are exhibited in this section in the tabular form and the obtained results are analyzed by the performance evaluation metrics. In the following Table 1, the confusion matrix for all the working classifier is presented. Total of 66 instances is used in the test case in our experiment. Table 1 presents the confusion matrix of the seven working classifiers.

Table 1. Confusion Matrix Result of the Seven Working Classifiers.

Classifier Name	TP	FN	FP	TN
Naïve Bayes	55	1	8	2
Multilayer Perceptron	49	7	6	4
Logistic	55	1	9	1
LWL	56	0	9	1
Random Forest	48	8	8	2
Random Tree	45	11	6	4
Part	51	5	4	6

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All the seven standard performance evaluation metrics are calculated from the above-related equation (Equation 3 to 9) with the help of the value (TP, FN, FP, and TN) of the confusion matrix. Table 2 represents all of this calculated result.

TABLE 2. Experimental result of seven classifiers in terms of seven above-mentioned performance evaluation metrics. The competent classifier for this work is highlighted.

Classifier Name	Accuracy	Sensitivity/ Recall	Specificity	Precision	F1 Score	FPR	FNR
Naïve Bayes	86.36%	98.21%	20.00%	87.30%	92.43%	80.00%	1.79%
Multilayer Perceptron	80.30%	87.50%	40.00%	89.09%	88.29%	60.00%	12.50%
Logistic	84.85%	98.21%	10.00%	85.94%	91.67%	90.00%	1.79%
LWL	86.36%	100.00%	10.00%	86.15%	92.56%	90.00%	0%
Random Forest	75.76%	85.71%	20.00%	85.71%	85.71%	80.00%	14.29%
Random Tree	74.24%	80.36%	40.00%	88.24%	84.12%	60.00%	19.64%
Part	86.36%	91.07%	60.00%	92.73%	91.89%	40.00%	8.93%

From Table 2, we observed that three classifiers namely Naïve Bayes, LWL, and Part outperforms than another four working classifiers and obtained the equal accuracy of 86.36%. Among Multilayer Perceptron, Logistic classifier, Random Forest, and Random Tree, Random Tree classifier performs worst and achieving the accuracy of 74.24%. If the data set does not have the equal data of several types (for this experiment, such as enrollment or dropout) and the cost of FP and FN are very much different, then accuracy cannot alone justify properly the performance of the model. In that case, we have to look into both the precision and recall which indicates to look into the F1 score [21]. Since our dataset has more records of enrollment compared to the dropout with the cost variation of FP and FN. And also the accuracy of Naïve Bayes, LWL, and Part are same and 86.36%. So we have to look into the F1 score. The F1 score of the three classifiers namely Naïve Bayes, LWL, and Part is 92.43%, 92. 56% and 91.89% respectively. Among these three classifiers, the Part classifier has the lowest F1 score. The Naïve Bayes and LWL have almost equal F1 score. So we can say both Naïve Bayes and LWL performs better in this context but LWL outperforms among all the classifiers.

V. CONCLUSION

In this work, seven (7) classifier algorithms are used to predict the enrollment and the dropout or incompletion of post-graduation degree of the individual. Naïve Bayes, Multilayer Perceptron, Logistic Regression, LWL, Random Forest, Random Tree, and Part classifier are used here. Among these seven (7) classifier, Naïve Bayes, LWL, and Part classifier acquired 86.36% accuracy and outperforms than Random Forest, Multilayer Perceptron, Logistic Regression, and Random Tree classifier. Among all the classifier, Random Tree classifier is performed lower than any other classifier algorithms with an accuracy of 74.24%.
After analysis of results based on seven performance evaluation metrics, we found that LWL classifier performed best among all the classifiers. In the future, we want to add more features in our data set with the more student data than the present dataset. We also try to collect the dataset from more than one university and apply more classifier algorithms to the dataset.

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