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Registration Status Prediction of Students Using Machine Learning in the Context of Private University of Bangladesh

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Abstract: ***Bangladesh is a densely populated country where a large portion of citizens is living under poverty. In Bangladesh, a significant portion of higher education is accomplished at private universities. In this twenty-first century, these students of higher education are highly mobile and different from earlier generations. Thus, retaining existing students has become a great challenge for many private universities in Bangladesh. Early prediction of the total number of registered students in a semester can help in this regard. This can have a direct impact on a private university in terms of budget, marketing strategy, and sustainability. In this paper, we have predicted the number of registered students in a semester in the context of a private university by following several machine learning approaches. We have applied seven prominent classifiers, namely SVM, Naive Bayes, Logistic, JRip, J48, Multilayer Perceptron, and Random Forest on a data set of more than a thousand students of a private university in Bangladesh, where each record contains five attributes. First, all data are preprocessed. Then preprocessed data are separated into the training and testing set. Then, all these classifiers are trained and tested. Since a suitable classifier is required to solve the problem, the performances of all seven classifiers need to be thoroughly assessed. So, we have computed six performance metrics, i.e. accuracy, sensitivity, specificity, precision, false positive rate (FPR) and false negative rate (FNR) for each of the seven classifiers and compare them. We have found that SVM outperforms all other classifiers achieving 85.76% accuracy, whereas Random Forest achieved the lowest accuracy which is 79.65%.***

Keywords: ***Private University, Machine Learning, Registration Status, Prominent Classifier, Performance Evaluation Metrics.***

I. INTRODUCTION

Higher education can play a significant role in the development of a country. In Bangladesh, the cumulative number of students is higher compared to the number of institutions. At present, the total number of private universities is higher than the total number of public universities. The total number of private university in Bangladesh is now one hundred three [1] and the total number of public universities in Bangladesh is now forty-five [2]. Therefore, private universities have more students compared to the students of public universities. So, now the concerning matter is not the total number of students but the quality. A well-reputed university must assure the quality of education for the students. For providing a quality educational environment, some emerging preplanned steps are necessary. Early prediction of the total number of registered students in a particular semester of a year can help to boost up this preplanned by creating an impact on the budget, marketing strategy, and sustainability of a private university.

Here, this research mainly focuses on to predict the student registration status in the context of the private university of Bangladesh. The scenario of the registration process of students is shown in Fig.1. At first, at the beginning of the first semester, the students can enroll in a semester by registering process. Then only the passed out students can enroll/register in the next semester. From all the enrolled students in the first semester, some of the students are dropped out. From all the dropped out students, some of them are revived back through improvement examination. This process is continuing for a student till completion of the final semester. All the parameters are selected in the context of a private university. Selected parameters are the number of D grade, the number of F grade, number of I grade, total due amount, and registration status. Data is collected from a renowned private university. The grading policy of this university as follows: F grade means marks between 0% to 39%, D grade means marks between 40% to 44%, I grade means the student did not complete or seat in the examinations, registration status indicates the enrollment/registration status to the next semester or not. We have performed several machine learning techniques on the data. From all the classifiers, support vector machine (SVM) achieved the highest accuracy than other classifiers. In this research, we have mainly applied seven machine learning classifiers namely SVM, Naïve Bayes, Logistic, JRip, J48, Multilayer Perceptron, and Random Forest to predict the registration status of the student in a semester. The rest of the research paper is ordered as regards: **Section II** describes the literature review. **Section III** outlines the methodology which is used here. **Section IV** exhibits the experimental results and details discussions of the result. Finally, **Section V** combines every finding and concludes this research work by mentioning future work.

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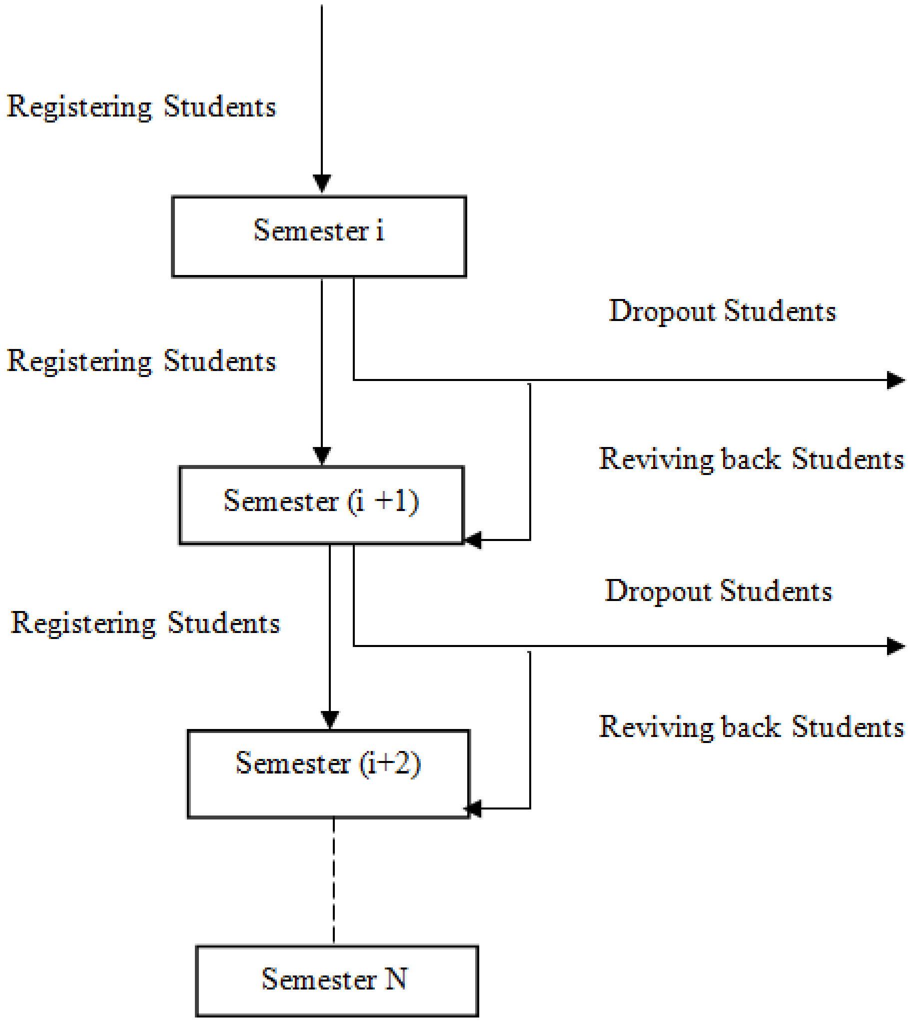

Fig. 1: Scenario of student registration process in the context of the private university of Bangladesh.

In Fig 1, i = 1, 2, 3, …., N. where N = final number of semester.

II. LITERATURE REVIEW

Yukselturk et al. [3], applied four approaches of data mining i.e, Naive Bayes (NB), *k*-Nearest Neighbour (*k*-NN), Neural Network (NN), and Decision Tree (DT) to classify the dropout students. In the time of implementation, they used 10-fold cross-validation method. The sensitivities of detection for NN, *k*-NN, NB, and DT were 87%, 76.8%, 73.9%, and 79.7%, respectively.

Tan et al. [4], developed prediction models using decision tree (DT), bayesian networks (BNs), and artificial neural network (ANN). A huge data sample of students was used in the time of the model training and model testing. The results were displayed and showed that the decision tree performed a better performance.

Liang et al. [5], performed dropout prediction on Massive Open Online Course (MOOC). Data of 39 courses were collected from the XuetangX platform which was based on the open-source Edx platform. 89% accuracy was achieved in dropout prediction tasking with the gradient boosting decision tree model.

Mulyani et al. [6], stated that Least Square Method can be applied to predict the number of new student's enrollment for the upcoming period based on the previous year's student data because it produced valid results to the actual results. This work showed 97.8% validity for the last three years.

Slim et al. [7], identified several factors that affect the enrollment of students and applied machine learning procedures to analyze the enrollment predictability of such factors. They mainly applied support vector machines and semi-supervised probability methods and logistic regression (LR). The results showed that a little set of factors were correlated to a student and college characteristics were highly related to the enrollment decision.

Abelt et al. [8], analyzed the applicant's history of UVa and recognized characteristics of a student that make more or less likely to enroll. They applied the neural network, logistic regression, and classification and regression tree models. They stated that the logistic regression model works better than other models to predict total undergraduate enrollment.

Biswas et al. [9], applied seven machine learning classifiers to predict the dropout and enrollment in the post-graduation degree. First, they computed the confusion matrix for each of the classifiers. Then by using the result of the confusion matrix, they calculated the value of seven evaluation metrics for each of the seven machine learning classifiers. After analysis the result of the working classifier, they stated that locally weighted learning outperforms all the classifiers.

Burgos et al. [10], proposed the adoption of knowledge discovery techniques to investigate historical course grade data of students to predict whether an individual will drop out of a course or not. For classification, logistic regression models are adopted. Experiments confirmed the predictive power of their proposal. They have devised a tutoring action plan using the resulting predictive models. By implementing this plan, they succeeded to decrease the rate of the dropout by 14%.

Willging et al. [11], stated that there are several causes of students to drop out of the college courses, but these reasons may be unique for student's enrollment in an online program. Several factors namely disconnectedness, technological problems, and issues of isolation that may lead to drop a course. They developed a survey that is online to collect student's data of the online program who dropped out. To compare many factors between who continue and those who drop out in the program, a logistic regression investigation was employed. The results showed that the reasons for individuals drop out in this regard are diverse and unique.

Wanjau et al. [12], proposed a general framework for mining student data enrolled in Science, Technology, Engineering and Mathematics (STEM) using performance weighted ensemble classifiers. They compared their technique with single model-based techniques and determined that it not only gives better accuracies in the abovementioned context but also more useful for understanding the several factors that influence the enrollment of the student in STEM.

Lestari et al. [13], presented a comparison between the two data mining classification techniques. They executed the two algorithms namely naïve bayes and C4.5 on a non-written enrolment system. The work showed that the accuracy of the naïve bayes classification technique is more prominent than another algorithm.

P´erez et al. [14], illustrated the results of an educational data analytics case study concentrated on the dropout detection of systems engineering undergraduate students after six years of enrollment. Primary data is prolonged and improved using an engineering process which is known as a feature engineering process. Their experimental results exhibited that simple algorithms can achieve stable levels of accuracy to recognize the dropout predictors. Results of algorithms namely decision trees, logistic regression, naïve bayes, and random forest were analyzed here to propose the most suitable option. Here also, Watson analytics is evaluated to ascertain the service usability for a non-expert user. The main results are shown here to decrease the rate of dropout by recognizing potential causes. Besides, they presented some judgments related to the quality of data to develop the student's data gathering process.

Koutina et al. [15] examined the most skilled machine learning approach for the final grade prediction of postgraduate students of Informatics of Ionian University. To perform this work, five courses (academic) were picked and each forming a specific dataset. Here, six popular machine learning classification algorithms were used. Machine learning classification algorithm namely naïve bayes and 1-NN showed the most outstanding results and which are very pleasing comparatively.

Aulck et al. [16], described initial attempts to model the dropout of students using the massive recognized dataset. Their results highlight various early signs or pointers of student attrition and showed that student's dropout can be correctly predicted even when predictions are performed based on a single term of academic transcript data. These outcomes highlight the potential for machine learning to have a consequence on the retention of students and success.

Mi et al. [17], proposed some temporal models for solving the dropout prediction problem. In particular, based on extensive experiments directed on a couple of massive open online courses (MOOCs) offered on edX and Coursera. The results showed that a recurrent neural network model with LSTM cells beats the baseline methods as well as our other proposed methods. They stated that they can take their work moreover by one plausible extension to the model that is to add a max-pooling layer before the output layer. They expected that their extension of the model helps to improve their model robustness.

An enrollment prediction study using support vector machines and rule-based predictive models was described by Aksenova et al. [18] and the goal of this work is to predict the total enrollment headcount that is composed of continued, returned, and new (freshman and transfer) students. The suggested strategy develops predictive models for continued, returned, and new students, respectively first, and then aggregates their predictive results from which the model for the total headcount is created. The types of data used during the mining process include population, employment, high school graduates, household income, tuition and fees, and historical enrollment data. Machine learning technique namely SVM produces the primary predictive results, which are then utilized by a tool named Cubist to produce easy-to-understand rule-based predictive models. Finally, they presented some experimental results on the prediction of enrollment for students.

III. METHODOLOGY

Here, the methodology section is mainly partitioned into three subsections namely, A) Dataset Description, B) Implementation Procedure, C) Performance Evaluation Metrics. The details description of this subsection is given below.

A. Dataset Descriptions: To accomplish this research work, we have used the real data which is collected from a renowned private university in Bangladesh. In this work, we have worked with five attributes. Among five attributes, four attributes are considered as the independent variable and one attribute is considered as the dependent variable. The number of D grade, the number of I grade, the number of F grade, and the total due amount of a student are the independent variables. On the other hand, registration status is the dependent variable. In the time of implementation, we have taken 66% data among all the data as a training dataset and the rest of the 34% data among all the data as a testing dataset.

B. Implementation Procedure: For predicting the registration status, we have used seven classifiers namely SVM, Naive Bayes, Logistic, JRip, J48, Multilayer Perceptron, and Random Forest. We have also calculated the six well-known performance evaluation metrics (accuracy, sensitivity, specificity, precision, FPR, and FNR) for each of the classifiers to measure the performance of each classifier in this context. To implement this work, we have followed the approach stated in Fig. 2.

Firstly, we have collected the raw data. After collecting the raw data, data should be processed, so we have performed preprocessing on the raw data to prepare the dataset. Then we have applied all the seven working classifiers namely, SVM, Naïve Bayes, Logistic, JRip, J48, Multilayer Perceptron, and Random Forest. Before training the classifier, we have separated the preprocessed dataset into the training dataset and the testing dataset. Because it is good to measure the accuracy of the classifier on the test dataset consisting of class-labeled tuples that were not utilized to the training of the classifier [19]. In this work, 66% of data are kept for the training of the classifier and the rest of the 34% data are kept for testing the classifiers' performance. All seven classifiers are trained on the training data set. After finishing the training of the classifiers, then we have performed the testing of the trained model with the help of the test dataset. Then, the best classifier is chosen with the help of the performance evaluation metrics.

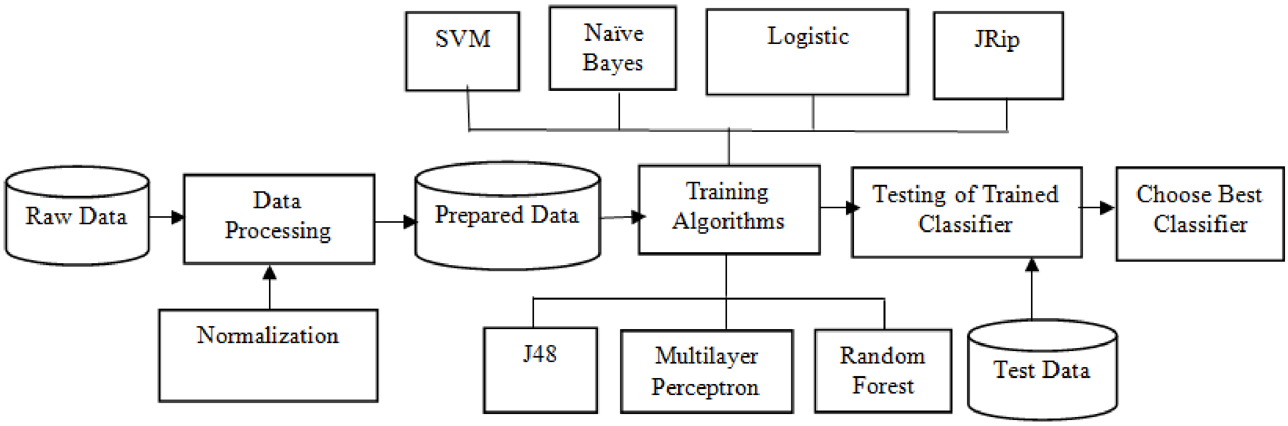

Fig. 2: Approach followed for student registration status prediction.

C. Performance Evaluation Metrics: The six well-known performance evaluation metrics are defined through the confusion matrix. The confusion matrix is known as an *M * M* matrix, where *M* = number of classes being predicted [20]. This work is mainly a two-class problem. So, each classifier mainly generates a 2 X 2 confusion matrix. The confusion matrix mainly consists of the True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). In our work, TP, TN, FP, FN denotes as follows.

True Positives: The situation when the classifier predicts the positive registration status of a student and also the actual output indicates the positive registration status of a student.

False Positives: The situation when the classifier predicts the positive registration status of a student but the actual output indicates the negative registration status of a student.

False Negatives: The situation when the classifier predicts the negative registration status of a student but the actual output indicates the positive registration status of a student.

True Negatives: The situation when the classifier predicts the negative registration status of a student and also the actual output indicates the negative registration status of a student.

The metrics such as accuracy, precision, specificity, sensitivity, false positive rate (FPR), and false negative rate (FNR) can be calculated by using the confusion matrix [21]. Accuracy of the classifier is also known as the recognition rate. Although the accuracy of the classifier is a specific measure, the word accuracy is also applied as a general term to refer to the predictive abilities of the classifier [19]. The sensitivity of the classifier is also known as the true positive rate or recall. The specificity of the classifier is known as the true negative rate. The six well-known performance evaluation metrics are presented by the following equations.

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+FP+TN} \times 100\% \quad (1)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100\% \quad (2)$$

$$\text{Specificity} = \frac{TN}{FP+TN} \times 100\% \quad (3)$$

$$\text{Precision} = \frac{TP}{TP+FP} \times 100\% \quad (4)$$

$$\text{FPR} = \frac{FP}{FP+TN} \times 100\% \quad (5)$$

$$\text{FNR} = \frac{FN}{FN+TP} \times 100\% \quad (6)$$

IV. RESULT AND DISCUSSION

In this section, the experimental result and the discussion of the obtained result of our work are presented. The result of the confusion matrix of seven classifiers is tabulated in Table- 1. Since it is a two-class problem, so the classifiers generate a 2*2 matrix. From the value of the confusion matrix, later we have computed the six performance evaluation metrics namely, accuracy, sensitivity, specificity, precision, FPR, and FNR with the help of above equation 1 to equation 6 and the result of the computed six performance evaluation metrics is shown in this section. These six performance evaluation metrics indicate the classifier's performance or the predictive capability of the classifiers in this context. Here, training dataset is the 66% data of the total dataset and testing dataset is the 34% data of the total dataset. The result of the confusion matrix is generated for the 344 instances of the students because of 34% test data.

Table- 1: Confusion matrix of seven classifiers.

Classifier Name	True Positive (TP)	False Negative (FN)	False Positive (FP)	True Negative (TN)
SVM	254	03	46	41
Naive Bayes	242	15	49	38
Logistic	251	06	54	33
JRip	253	04	65	22
J48	248	09	59	28
Multilayer Perceptron	249	08	60	27
Random Forest	234	23	47	40

In the time of implementation, 344 student's instances are put into the testing set where the actual registration status of 257 students is yes or positive. On the other hand, the actual registration status of 87 students is no or negative. After implementation, we have found a confusion matrix for each classifier which is stated in Table- 1. Now, we will explain the experimental result of the confusion matrix in detail for the most competent classifier and the worst classifier.

From Table- 1, we can see that the support vector machine classifier is correctly able to predict that 254 students will be completed their registration among 257 students. So the rest of the 3 students among the 257 students are incorrectly classified that they will not do their registration. On the other hand, this classifier is correctly able to predict that 41 students will not be completed their registration among 87 students. So the rest of the 46 students among the 87 students are incorrectly classified that they will do their registration.

From Table- 1, we can see that the Random Forest classifier is correctly able to predict that 234 students will be completed their registration among 257 students. So the rest of the 23 students among the 257 students are incorrectly classified that they will not do their registration. On the other hand, this classifier is correctly able to predict that 40 students will not be completed their registration among 87 students. So the rest of the 47 students among the 87 students are incorrectly classified that they will do their registration.

The details of the classifier's performance are possible to measure by calculating the abovementioned six well-known performance evaluation metrics. We have calculated the six well-known performance evaluation metrics i.e., accuracy, sensitivity, specificity, precision, FPR, and FNR for each classifier by using the data of the experimental confusion matrix. The result comparison among seven classifiers based on six standard performance metrics is presented in Table- 2.

Table- 2: Comparison of seven classifier's results based on six performance evaluation metrics.

Classifier Name	Accuracy	Sensitivity	Specificity	Precision	FPR	FNR
SVM	85.76%	98.83%	47.13%	84.67%	52.87%	1.17%
Naive Bayes	81.40%	94.16%	43.68%	83.16%	56.32%	5.84%
Logistic	82.56%	97.67%	37.93%	82.30%	62.07%	2.33%
JRip	79.94%	98.44%	25.29%	79.56%	74.71%	1.56%
J48	80.23%	96.50%	32.18%	80.78%	67.82%	3.50%
Multilayer Perceptron	80.23%	96.89%	31.03%	80.58%	68.97%	3.11%
Random Forest	79.65%	91.05%	45.98%	83.27%	54.02%	8.95%

From Table- 2, support vector machine (SVM) achieved higher accuracy than all the classifiers and random forest achieved the lowest accuracy among all the classifiers. Accuracy of support vector machine (SVM) is 85.76% which is good enough. Random Forest achieved the lowest accuracy of 79.65% which is low enough compared to SVM. The sensitivity of the Support Vector Machine classifier is 98.83% which is the highest sensitivity among all the classifiers. Sensitivity is the ratio of accurately predicted positive observations of all the observations in the actual class. SVM has 98.83% sensitivity means that it can identify 98.83% of students do the registration in the next semester. The specificity of the support vector machine classifier is 47.13% which indicates the classifier performs well enough among all the classifiers. Specificity means the true negative rate. In this works, the specificity of a classifier refers to how well a classifier identifies students who do not do registration in the next semester. SVM has 47.13% specificity means that it can identify 47.13% of students do not do registration in the next semester. Precision indicates how accurate the working model is out of those predicted positive, how many of them are actually positive. If the costs of False Positive (FP) are high, then precision is a good measure. In this work, the precision of SVM is 84.67%. False Positive Rate (FPR) of SVM is 52.87% which is lower than other classifiers. It indicates that the model performs comparatively well. False Negative Rate (FNR) of SVM is 1.17% which is the lowest among all the classifiers. So, from the analysis of the performance evaluation metrics, we can say that the performance of the Support Vector Machine is very significant among all the working classifier.

V. CONCLUSION AND FUTURE WORK

Here, several machine learning techniques are applied in the context of the private university of Bangladesh to predict the registration status of the students and the classifier's performance is evaluated by the six standard performance evaluation metrics. We have considered five attributes here to accomplish this work. Based on these features, we have been able to achieve the desired result. We have applied seven machine learning classifiers. Among all the classifiers, Support Vector Machine (SVM) provides the best result and the achieved accuracy of SVM is 85.76% which is good enough and the result of the other five performance evaluation metrics of the SVM is also significant. On the other hand, Random Forest achieved the lowest accuracy and the achieved accuracy is 79.65%. The result of the other performance evaluation metrics of Random Forest is not so significant compared to SVM. In the future, we will consider more attributes and more semester data with the increasing number of the university.

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