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Educational data mining model using support vector machine for student academic performance evaluation

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ABSTRACT

In the educational landscape, educational data mining has emerged as an indispensable tool for institutions seeking to deliver exceptional and high-quality education. However, education data revealed suboptimal academic performance among a significant portion of the student population, which consequently resulted in delayed graduation. This experimental research generally aims to evaluate student graduation outcomes. Meanwhile, the specific aim is to predict student academic performance by applying the support vector machine (SVM) model based on sampling techniques. The proposed model is evaluated using datasets originating from one of the State Islamic Universities. The dataset has both on-time and delayed graduation status. The results show that the support vector machine model based on the shuffle sampling on the Arabic language and literature (BSA) dataset produces excellent performance on both tests with accuracy values above 90% and area under the curve (AUC) above 0.9. Meanwhile, the Islamic education management (MPI) dataset produces excellent performance when applying a support vector machine based on stratified sampling with accuracy values above 90% and AUC above 0.9. Therefore, it could be concluded that the proposed model has excellent and reliable performance.

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1. INTRODUCTION

The process of mining educational data is called educational data mining (EDM). The research field of educational data mining is crucial in education for discovering patterns in knowledge in large data sets. This is a necessity to increase the effectiveness and success of an institution or educational institution. A review of studies has highlighted academic performance, especially in measuring the performance of students in higher education [1]. Many students have academic performance that is not optimal, thus many students do not graduate on time [2]. This can be influenced by various factors, including social, and geographic, demographic characteristics.

The education system has experienced extraordinary improvements with the existence of artificial intelligence (AI) which can make things easier for teachers and students. Improving learning can also be done with AI technology to motivate students to learn [3]. The education sector currently uses a lot of AIs integrated with educational data mining to extract information in the form of knowledge and patterns from large data stores using machine learning. Therefore, evaluating student performance is very important for conducting research [4].

Recently, considerable literature has grown around the theme of educational data mining to overcome problems such as learning motivation, delays in completing studies, drop-outs, and so on. These problems can be overcome using decision tree (DT) models [5], developing learning achievement [6], assessment [7], and identifying understanding of particular concepts [8]. In addition, machine learning algorithms are widely applied in educational data mining for the prediction of student payment behavior [9]. Predicting academic performance to decrease student academic failure and enhance the quality of education [10], predicting student performance using e-learning data [11] for decision-making, and predicting student academic achievement using the neuro-fuzzy approach technique [12]. Prediction using the artificial neural network (ANN) method is widely used [13]–[16], deep learning [17], random forest, and synthetic minority over-sampling technique (SMOTE) [18]. Class imbalance with undersampling, oversampling, and SMOTE [19] as well as ensemble.

Abdelmagid and Qahmash [20] conducted research with clustering and prediction of student academic performance. Clustering is carried out using the *k*-means model to obtain a pattern from a series of electronic courses, while the linear regression (LR), random forest (RF), *k*-nearest neighbors (*k*-NN), tree, and support vector machine (SVM) models are used to make predictions. The results obtained from these various algorithms, namely linear regression, have very high performance. In study by Holicza and Kiss [21] student performance was evaluated by predicting, testing, and providing reasons. The method used to solve this problem uses machine learning algorithms such as SVM, DTs, RF, and *k*-NN. The results found that habits like sleep, study time, and screen time are related to school success. Alhazmi and Sheneamer [22] has identified the impact of student performance using clustering and classification techniques. The clustering technique used is t-distributed stochastic neighbor embedding (T-SNE) to reduce the dimensions of the initial dataset. Meanwhile, the classification techniques used to predict are eXtreme gradient boosting (Xgboost), logistic recognition, SVM, *k*-NN, and RF.

Hussain and Khan [23] conducted a study that used a regression model to estimate grades and a DT as a classification model to predict student performance. Genetic algorithms are applied for feature selection. The results indicate that the genetic algorithm (GA) and DT machine learning algorithms have efficient and relevant results. Xue and Niu [24] proposed a multi-output hybrid integration model to predict student performance. The data used comes from the superstar learning communication platform. According to experimental results, the XGboost method is more accurate than the other comparison methods. Granados *et al*. [25] identified relevant variables and developed them with a machine learning algorithm, namely XGBoost, which was applied to classify two academic performances into good and regular categories.

Begum and Padmannavar [26] conducted a study with an evaluation of student performance in Portuguese language and mathematics subjects. The method used is RF optimized with Bayesian and *k*-NN. The dataset used is general and obtained from University of California, Irvine (UCI). The research results reached an accuracy rate of 87% and 73%. Yue *et al*. [27] conducted a study on student academic prediction using cost-sensitive feature selection and a multi-objective gray wolf optimizer. The dataset used comes from UCI. Zhao *et al*. [28] also developed a prediction model for academic performance using machine learning algorithms. Its research found differences in performance between machine learning methods. Thus, it is necessary to consider various factors in these methods even though all of them can be used well.

In a study by Martins *et al*. [29] the application of machine learning techniques has been developed for early detection of school dropouts in higher education. The model was built using undergraduate student data. Five machine-learning methods were used to train the model. Of the five models trained, the results show that the RF model which integrates the class imbalance technique has better performance. Latif *et al*. [30] proposed a combination of machine learning between classification algorithms with bagging and boosting ensemble techniques for predicting student performance and identifying students at risk. Modeling was carried out using six classification models with several classification categories, namely two classes, three classes, and four classes. The dataset used is digital electronic education and design suites (DEEDS) enhanced learning technology (ELT). The results obtained by binary classification have more satisfactory accuracy compared to other classification categories.

Qahmash *et al*. [31] predicted student performance using five classification models, namely DT, neural network (NN), RF, Naïve Bayes (NB), and *k*-NN which were supported by regression and optimization techniques as analysis to identify appropriate weights. The results of these predictions show that the classification performance of NN and NB has good performance compared to other performance algorithms. Jacob and Henriques [32] proposed several machine learning algorithms including DTs, *k*-NN, NNs, and SVM. This was done to predict students' academic success at the time of registration and the end of the first academic year. The prediction success was found in the NN algorithm with a performance achievement of 85% using historical data from undergraduates at the Portuguese business school. Alghamdi and Rahman [33] predicted the success of higher school students by applying three classification algorithm models, namely NB, RF, and J48. At the preprocessing level, the SMOTE technique is applied to overcome class imbalance and also extract features using correlation coefficients. Meanwhile, the greatest level of accuracy is in the NB classification model. Huang *et al*. [34] investigated student performance prediction using a hybrid method between SVM and ANN. SVM is used for binary classification. Meanwhile, ANN is used for multi-class classification. The results of the hybrid model provide effective value. Verma *et al*. [35] conducted a study using DT, NB, *k*-nearest neighbor, SVM, and RF classification techniques. Bagging techniques are combined with classification techniques to improve the performance of classification models. The NB model has the best performance than other classification models and its performance is further improved based on bagging techniques. Accuracy results achieved from 89% increased to 91%. In another study by Sarwat *et al*. [36] a conditional generative adversarial network (CGAN) was proposed to overcome the use of relatively small datasets. This was done to increase the data sample by creating synthetic data. Meanwhile, the SVM classification model is used to predict student performance. As a result, the application of CGAN and SVM proved to be effective.

Different from previous research above, in this study the data used came from one state higher education institution with two study programs. In a collection of databases, data is selected for several important features that can be evaluated based on a classification model. Among the features selected and used are the final grades for each semester (from semester one to semester eight). Two sampling techniques, namely shuffle and stratified, are applied to produce accurate and effective training data. Meanwhile, a SVM is selected and applied to build a classification model. This study aims to evaluate student academic performance by applying the SVM classification model based on sampling techniques. There are four parts to this paper. This section marks the beginning of the introduction, which explains the topic of educational data mining. In addition, it concerns research methods. Moreover, it encompasses results and discussions that provide the results of the experiment along with explanations. Furthermore, in conclusion, namely concluding the results and discussion.

2. RESEARCH METHOD

This study is structured into multiple research stages. This stage consists of data collection, data processing, method proposal, experimentation and model testing, and performance evaluation. This research method is also equipped with a scheme of experimental settings shown in Figure 1.

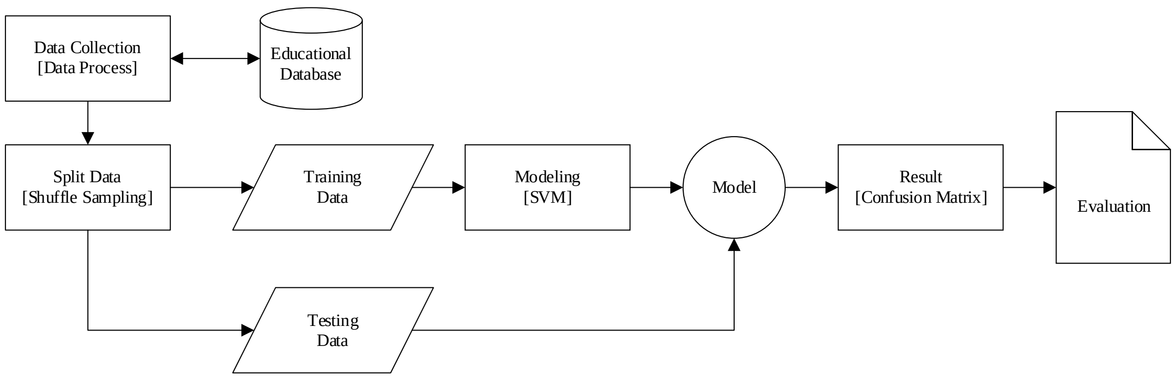


Figure 1. Scheme of experimental settings

2.1. Scheme of experimental settings

Figure 1 presents a summary of the experimental scheme settings. To begin with, the educational database has a large data capacity. Next, the collected data is processed and cleaned to obtain the dataset to be processed. After data collection was carried out, the data was split into two parts using stratified and shuffle sampling techniques to obtain training data and testing data. After splitting the training data, it is applied to a classification model, namely the SVM algorithm. After the model is created, it is tested with test data. The testing results yield a predictable pattern in the form of a confusion matrix. Then the results are evaluated based on their performance and accuracy.

2.2. Data collection

In the data collection process, data is extracted from the database of one of the state's higher Islamic education institutions. The study program data obtained is the Arabic language and literature (BSA) and Islamic education management (MPI) study program database. Data is obtained from the study results of students who have been declared graduated based on graduation date. Graduation result data is cleaned from noise and inconsistent problems. Next, integrate data from various sources. After that, the data is selected based on relevant data from the analysis results. Next, the data is transformed into data mining to be extracted into knowledge or patterns. Patterns are evaluated based on the identification of interesting points of knowledge.

Based on the results of student performance evaluations in each semester, data processing is carried out from the first semester grades to the final semester. This value is calculated between the total weight value multiplied by the number of credits to get the semester achievement index value. The semester achievement index used is labeled on time and delayed based on graduation provisions. Graduation requirements are based on a shorter length of study equal to four years or eight semesters. From the results of these provisions, on-time graduation labeling was carried out on both BSA and MPI datasets. As for graduating on time and delayed for BSA studies, there were 142 samples consisting of 60 samples of students who graduated on time and 82 who passed delayed. Meanwhile, for the MPI dataset, there are 81 samples consisting of 53 who graduated on time and 28 who passed delayed. The dataset characteristics of the samples utilized can be viewed in Table 1.

Table 1. Details about the dataset

#	Features	Types	Descriptions
1	IPS-1	Real	GPA 1
2	IPS-2	Real	GPA 2
3	IPS-3	Real	GPA 3
4	IPS-4	Real	GPA 4
5	IPS-5	Real	GPA 5
6	IPS-6	Real	GPA 6
7	IPS-7	Real	GPA 7
8	IPS-8	Real	GPA 8
9	Class	Binominal	On-time or delayed

Table 1 contains the characteristics of the dataset which consists of the cumulative achievement index for semesters one to eight with the type of data used being integer and nominal for labels or classes. The data collection that has been carried out becomes a dataset that is ready to be transformed for modeling using training data. The sharing of training data was carried out using stratified and shuffle sampling techniques [37]. Distribution of training and testing data in proportions of 80:20 and 70:30 for both sampling techniques. Stratified sampling is the process of stratified sampling that generates random subsets and guarantees that the distribution of classes in the subsets is identical to that of the entire example set. In binary classification models, stratified sampling creates random subsets that have proportions of the two values of the class labels that are roughly equivalent. Meanwhile, shuffle sampling is random subsets of the example set are created using shuffled sampling. Examples are randomly chosen to create subsets.

2.3. Proposed method

In this section, SVM as a machine learning technique is proposed. This algorithm can be used in regression and classification models. The SVM algorithm has the advantage of being an algorithm that has flexibility, robustness, and overfitting resistance in handling pattern recognition in data mining [38] which can be used in the areas of computer science, statistics, and mathematical optimization theory. The SVM algorithm supports various types. In this study, SVM was used to evaluate student graduation according to study time accuracy using a classification model.

2.4. Experiments and model testing

In this section, the experimenter uses a computer platform with the Windows 11 operating system which is equipped with analysis tool in the form of the RapidMiner application. The tool is used to train training data on a model which is then tested with testing data to evaluate student academic performance. The model used is a SVM based on sampling techniques.

2.5. Performance evaluation

The performance evaluation in this research is determined by accuracy, precision, recall (sensitivity), F-measure, and area under curve (AUC). This evaluation is produced from a classification model in the form of a confusion matrix which can be seen in Table 2. Next, the confusion matrix is calculated based on a formula. Accuracy is the proportion between the target classification or class that is classified correctly (1). Precision is identifying the accuracy of the binary classification model when predicting a target or class that has a positive value (2). Recall is identifying all possible targets or classes that have positive values (3). F-measure is a measurement of the accuracy of a binary classification model by considering precision and recall for test scores (4). AUC is a receiver operator characteristic (EDM) curve with limits on independent values. In cases where positive samples are categorized correctly and negative samples are categorized incorrectly.

$$Accuracy\ (Acc) = \frac{TP+TN}{TP+FP+FN+TN} \tag{1}$$

$$Precision\ (PPV)\ = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = Sensitivity\ (SN)\ = \frac{TP}{TP+FN} \tag{3}$$

$$F-measure\ (F)\ = \frac{2TP}{2TP+FP+FN} \tag{4}$$

Table 2 shows an overview of confusion matrix. True positive (TP): a target that is predicted to be "delayed", but is "delayed"; False positive (FP): a target that is predicted to be "delayed", but is "on time"; False negative (FN): a target that is predicted to be "on time", but is "delayed"; True negative (TN): a target that is predicted to be "on time", but is "on time". Otherwise, the AUC evaluation criteria are as follows: Excellent (0.90-1.00); Good (0.80-0.90); Fair (0.70-0.80); Poor (0.60-0.70); and Failure (0.50-0.60)

Table 2. Confusion matrix

Predicted	Actual	
	Delayed	On-Time
Delayed	TP	FP
On-Time	FN	TN

3. RESULTS AND DISCUSSION

In this research, experiments were carried out using a computer platform with specifications Intel® Core™ i3-8130U 2.20 GHz (4 CPUs), 8 GB RAM, Windows 11 operating system, and RapidMiner version 10.1.003. Experiments were carried out on both BSA and MPI datasets using SVM algorithms based on stratified and shuffle sampling. The experimental results on each dataset produce a confusion matrix and these results have been completely evaluated as shown in Table 3.

Table 3. Results of the confusion matrix

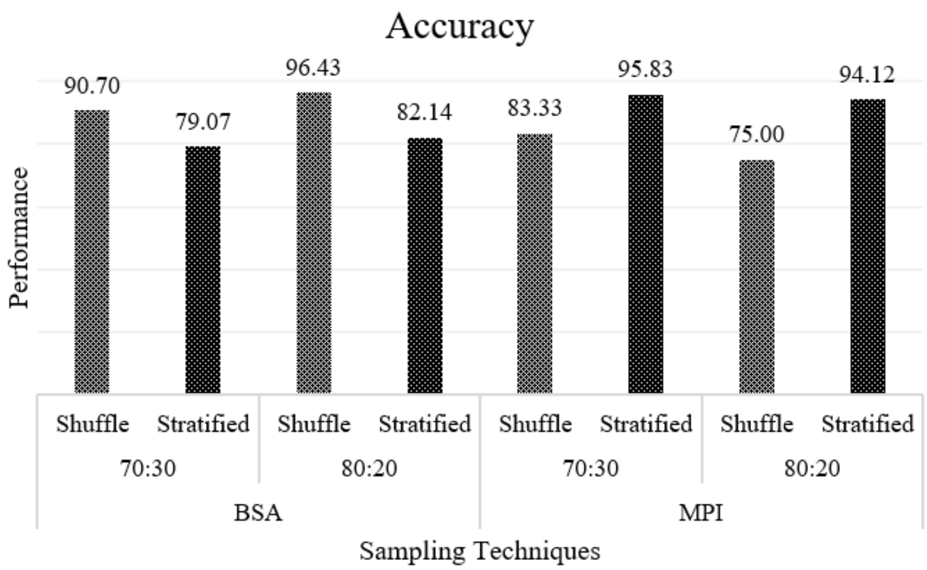
Dataset	Split	Sampling	TP	FP	FN	TN	Recall	Precision	F	Accuracy	AUC
BSA	70:30	Shuffle	23	1	3	16	88.46	95.83	92.00	90.70	0.941
		Stratified	19	3	6	15	76.00	86.36	80.85	79.07	0.858
	80:20	Shuffle	16	0	1	11	94.12	100.00	96.97	96.43	0.984
		Stratified	13	2	3	10	81.25	86.67	83.87	82.14	0.870
MPI	70:30	Shuffle	7	0	4	13	63.64	100.00	77.78	83.33	0.923
		Stratified	7	0	1	16	87.50	100.00	93.33	95.83	0.984
	80:20	Shuffle	2	0	4	10	33.33	100.00	50.00	75.00	0.850
		Stratified	5	0	1	11	83.33	100.00	90.91	94.12	0.985

Table 3 In the experiment using the BSA dataset, the results of the confusion matrix calculation on testing 30% of data using the shuffle sampling technique produced a recall value of less than 90%. Meanwhile, precision, F-mesure, accuracy above 90%, and AUC above 0.9 are classified as excellent. In the experiment using the stratified sampling technique, the resulting value was lower than the shuffle sampling technique. Still in the experiment using the BSA dataset, testing 20% of data on all measurements produced

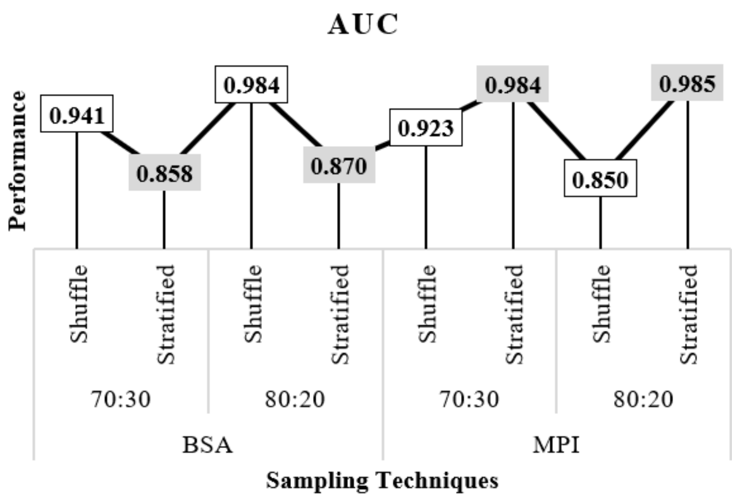
values above 90%, but the precision results reached 100%, and for AUC above 0.9, it was classified as excellent. In testing using the BSA dataset, the shuffle technique is superior to the stratified technique.

In the experiment using the MPI dataset, the values produced from the confusion matrix using the stratified sampling technique using 30% testing data with a recall value of less than 90%, for F-measure and accuracy above 90%. Meanwhile, precision reaches 100%, and AUC is above 0.9 as classified excellent. In the shuffle sampling technique, the resulting value is not as good as the stratified sampling technique, however, the precision results reach a value of 100%. On the other hand, testing 20% data using the stratified technique has almost the same performance as testing 30% data, which is better than the shuffle technique. And for AUC values above 0.9 are as classified excellent. In testing using the MPI dataset, the stratified technique is superior to the shuffled technique.

Figure 2 illustrates a performance comparison of the SVM model based on sampling techniques. In Figure 2(a) accuracy and Figure 2(b) AUC. It can be seen that there are differences in results between the stratified and shuffle techniques for each testing data in the two datasets. On the BSA dataset, shuffled sampling techniques are more accurate for both testing data. However, 20% of samples are more effective in testing data than 30%. In contrast to the BSA dataset, on the MPI dataset, the stratified sampling technique is better than the shuffle sampling technique. However, 30% of samples are more effective in testing than 20%.



(a)



(b)

Figure 2. Performance comparison of SVM based on sampling techniques for (a) accuracy and (b) AUC

The results of this research have excellent performance on the SVM model based on sampling techniques which are used to evaluate student academic performance predictively. These results are in line with those of previous studies. For instance, applying models with sampling techniques such as SMOTE [18], [33] produces optimal performance in accuracy and AUC. In addition, the implementation of the XGboost model [25], gradient boosting machine (GBM) grid model [9], CGAN with deep SVM [36], as well as ensemble techniques [35], [39] also have optimal performance in predicting students' academic performance.

In contrast to studies that apply a Bayesian-optimized [26] the resulting performance is inaccurate. Likewise, Likewise, the integrated ensemble techniques [11] for predicting student performance in e-learning data evaluation. In addition, a multi-output hybrid ensemble model was applied to predict the value in improving the quality and effectiveness [24] whose results were less than optimal. On the other hand, Alboaneen *et al*. [40] seems to confirm the findings, that academic factors can influence student academic performance. In another study, although various models have different performances, for evaluating academic performance it is necessary to consider factors that influence model performance [28].

4. CONCLUSION

This study evaluates student academic performance using an SVM model based on sampling techniques. The findings indicated that in the evaluation of the BSA dataset using the SVM model based on the stratified technique on both data tests, it performed as a good classification category. On the other hand, the SVM model based on the shuffle technique in both data tests obtained an excellent category. However, when testing the model using an 80:20 test data ratio, it produced more accurate performance than the others. Whereas, in the MPI dataset evaluation, the SVM model based on both stratified and shuffle techniques has an excellent performance. However, there is only one that produces a good category, namely the shuffle technique using a ratio of 80:20 test data. Thus, the application of the SVM model based on both sampling techniques can produce optimal performance in predicting student academic performance for evaluation. In addition, the performance of the SVM model is proven to be a strong and reliable model. Likewise, The sampling technique has been proven to be effective in sampling data accurately.

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