Educational Data Mining in Graduation Rate and Grade Predictions Utilizing Hybrid Decision Tree and Naïve Bayes Classifier

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Abstract: The use of Educational Data Mining (EDM) in educational context has the probability to frame the extant models of teaching and learning by affording new solutions to the interaction problem. An educational domain like student related prediction become so essential in the higher learning institutions since it able to be presenting the rate of the students' graduations. Through prediction, data is analyzing and able to afford big picture of trends and patterns for the management of the higher educations. Through this paper research we are presenting the utilization of the hybrid decision tree combined with the naïve Bayes classifier. The result showing the accuracy of prediction for graduation rate and graduation grade is 72.73% on the highest value partition.

1 INTRODUCTION

An advancement of focus in Artificial Intelligence boosted the improvement of data mining and analytic in the didactic sphere (Bhatia, 2019). Extracting the new aspects and patterns from huge data set applying the methods such as machine learning, statistics, and database systems is the data mining definition process (Sowmya and Suneetha, 2017). The main aim of data mining process is finding the recognizable and possibly advantageous information from abundant numbers of data sets (Lefebvre et al., 2016).

A special data mining field for techniques, tools, and researches that utilized to gain information from educational records, known as Educational Data Mining (EDM). An EDM works to represent the implementation of data mining in all educational sectors. They generate an environ that able to successively amass, handle, report and manage on digital data repeatedly in order to enhance the educational process. The use of EDM in educational context has the probability to frame the extant models of teaching and learning by affording new solutions to the interaction problem (Berland et al., 2014). Data mining has many methods according to its purposes and goals. In the EDM itself, the common problems to solve are analyzing the dropping out or retention analysis (Pradeep et al., 2015), virtual learning objects and virtual learning environment (Dutt et al., 2015), performance and student evaluation (Shukor et al., 2015), generation of educational recommendations (Chalaris et al., 2014), learning pattern identification (Mayilvaganan and Kalpanadevi, 2015), students pattern identification (Campagni et al., 2015), and students related prediction (Kaur et al., 2015).

Considering the EDM educational domains, the learning pattern identification indeed has the highest research interest among the others educational domains (Manjarres et al., 2018). However, it does not mean that others domain is not as important as learning pattern identification. Each domain lists have its own importance in accordance with the conditions of the research object. About the quantity of research conducted on a specific domain, is not a benchmark for the quality of a particular domain. An educational domain like student related prediction become so essential in the higher learning institutions since it able to be presenting the rate of the students' graduations (Kaur et al., 2015).

The prediction of rate graduation for students is important since today's education domain challenges are to provide positive experience for students, start from enrollment till graduation then beyond. Through prediction, data is analyzing and able to afford big picture of trends and patterns for the management of the higher educations. Hence, they can be evaluating and streamlining processes to create efficiencies, and boost the overall student experience (Mishra et al., 2014). Realizing that target, an appropriate data mining technique needs to be implemented solving the prediction of graduation rate for students.

By all of techniques in determine the educa-

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tional domains, especially for students related prediction (Patarapichayatham et al., 2012), the techniques such decision tree (Shukor et al., 2015), classification (Kaur et al., 2015), clustering (Dutt et al., 2015), sequential patterns (Campagni et al., 2015), bayesian networks (Sundar, 2013), neural networks (Shahiri et al., 2015), association rules (Belsis et al., 2014), and linear regression (Thai-Nghe et al., 2010) are familiars methods that utilizing on inspecting student related prediction.

The decision tree method creating the rule according to obtain fact. It is authoritative and eminent classification method as it has immense precision computational. However, the high accuracy of decision tree, impacting the more time-consuming process then another method like naïve bayes. The naïve bayes itself is the technique of elementary probability classification. It is predicting the future value according to the previous value (Farid et al., 2014).

The collaboration between the high accuracy of decision tree and the simplicity of naïve bayes to be implemented in the EDM is the work on this research. The educational domain as a research object is predicting graduation rate and predicate of the students. The result of this study aiming to help educational management process and improve the quality of solutions and the policies on the pedagogical implementation.

2 METHODS

2.1 Decision Tree

Decision tree is a popular classification method as it easy to interpreted. It is utilized for statistical pattern recognition. A decision tree has each mode that represents an attribute, to represent the decision it has branch, then to draw categorical it has leaf (Shahiri et al., 2015).

The main idea of decision tree is generating a tree that provides whole data and processes with an outcome at each leaf. Generating the decision tree method, these steps below is implemented:

- Tree construction
- Tree pruning (pre-pruning, post-pruning)
- Rule decision generated

2.2 C4.5 Algorithm

According to the availability of data trains, the C4.5 algorithm is applied. This algorithm is the advancement of ID3 algorithm. Some of developments done in C4.5 are handling problems of ID3 algorithm such the missing value, continue data, and training (Farid et al., 2014). The main steps of C4.5 algorithm is described as follows.

- Decide the attribute as root node and the attribute as next node. Root node is the attribute with the highest gain ratio (see equation 1).

$$gain(S,A) = entrophy(S) - \Sigma_{i-1}^{n} \frac{|Si|}{|S|} * Et \quad (1)$$

- Compute the value of entropy (see equation 2).

$$Entrophy(S) = \Sigma_{i=1}^{k} - p_i * log_2 P_i \quad (2)$$

- Compute the information split (see equation 3).

$$SplitInfo(S,A) = -\Sigma_{i=1}^{n} \frac{S_i}{S} log_2 \frac{S_i}{S} \quad (3)$$

- Compute the ratio gain (see equation 4).

$$GainRatio(S,A) = \frac{Gain(S,A)}{SplitInfo(S,A)} \quad (4)$$

2.3 Naive Bayes Classifier

In terms of accuracy and the efficiency of calculation on documents classification, the naïve bayes classification method is considered conceivably better measure with the other classification methods. Assuming all attributes in a dataset are separates, then it able to predict the future values based on pass values, it is the simplicity of naïve bayes classification technique (Sundar, 2013).

The advantage of naïve bayes technique is non timeconsuming data computation. It is enhancing the classification performance through throwing unnecessary attributes. However, this technique if compares with the other techniques of classification has poorer accuracy in some dataset (Renaningtias et al.,).

The formulation applying in naïve bayes is according to the bayes theory, describes as follows (see equation 5).

$$P(C_i|X) = \frac{P(C_i|X)P(C_i)}{p(X)} \quad (5)$$

To generate prediction utilizing the naïve bayes classifier technique, the steps is done as follows.

- Data transform into variables which each data represent by attributes of vectors with dimension of X=X1,X2, . . . , Xn.
- For class i, as C1, C2, . . . Cn are given data X to classify and predict if X is on the highest posterior group. In another word X to on C if P(Ci) > P(Cj)

- For constant P(X) if P(X—Ci) P(Ci) then calculated If probability is unknown then assumed class is the same, such as: P(C1)=P(C2)=...=P(Cn), compute P(X—Ci) and P(X—Ci)P(Ci).
- Reducing the unnecessary attributes of P(X—Ci), utilizing the equation 6.

$$P(X|C_i) = \prod_{k=1}^{n} p(x_k|C_i) = P(x_1|C_i) \qquad (6)$$

- P(X—Ci)P(Ci) is analyzed on every Ci to result the classification prediction from X. Equation 7 is used for handle this calculation.

$$PXCi), PCi > PXCj), PCj, for 1 \leq j \qquad (7)$$

The number of identical classes or labels on data are calculated, then it is the same as identical cases with same classes. According to its result, all class in same attributes is multiplied. Those result is showing prediction result of naïve bayes classification.

2.4 Hybrid Decision Tree and Naïve Bayes Classifier

Hybrid decision tree is established from C4.5 algorithm. The dataset for training is given as, D = {x1, x2, ..., xn} each training item is expressed as {A1, A2, ..., An}. For every attribute Ai, it is filling with the attribute values {Ai1, Ai2, ..., Ain}. The data use as a training data are fitting to set of classes C = {C1, C2, ..., Cm}.

In the generating the decision tree application, there are couple main steps as describe below.

- Builds training dataset, D
  Generating the decision tree, first is selecting the best splitting attribute with the maximum information gain value as the root node of the tree. After that, adding the child node and its arcs to the decision tree. The whole process is going on looping through adding new subtrees to any branching of the arc. It is end for the instance in the reduced training set all belong to the same class. Then it labeling the corresponding leaf node.
- Builds decision making according to the decision tree.
  Naïve Bayes classifier is utilizing to classify every training instance, xi ∈ D. Computing a previous probability, P(Ci), for every class, Ci ∈ D and the probability class of conditional P(Aij—Ci). After that any training instance is calculated utilizing the probability, which the training instance is, xi ∈ D. For selecting the class Ci, it is accordance with the highest posterior probability, P(Ci—Xi).

3 RESEARCH'S MATERIALS

On this research, the data that is utilized from Department of Communication, Universitas Bengkulu. Its data are the students' academic data, such as Grade Point Average (GPA), college entrance examination paths (through: SBMPTN (local selection), SNMPTN (national selection), PPA (academic selection), SPMU (invitation)), high school origin, major in high school, domicile, gender, scholarship, status, study duration, and graduation predicate. The total data is collected as 215 datasets, to be used for the data train.

4 PROCEDURES OF THE RESEARCH

Projects in data mining are done systematically. According to the best practice, researchers and practices on data mining are proposed some simple workflows to develop the success chance of working on data mining projects. A process that decided as a standard for data mining project is the Cross-Industry Standard for Data Mining (CRISP-DM).

On this study we are utilizing this popular CRISP-DM as the standard procedures on our research. Its steps are working as follows.

4.1 Data Cleanup and Integration

On this phase, the raw data that may have wanting records, noises, outliers and inconsistent data are cleaned to get missing values, data smoothness, finding outliers and fix inconsistency.

After data-cleaning complete, then its data are mixed with multi and various resources into one consistent data store, such as data warehouse. It is possible to data have some databases, files or data cubes.

4.2 Data Selection

Data selection on this phase is worked to decrease the number of redundant or irrelevant data.

4.3 Data Transformation

Done with the selection process then its time to transform the data into appropriate format that we utilized on this research. Our format of the data training, are describe below (see Figure 1).

Attribute	Code	Sub-Attribute	Annotation
GPA 1	0	≤ 2.00	Variable input
	1	≥ 2.00 – 2.75	
	2	≥ 2.76 – 3.00	
	3	≥ 3.01 – 3.50	
	4	≥ 3.51	
GPA 2	0	≤ 2.00	Variable input
	1	≥ 2.00 – 2.75	
	2	≥ 2.76 – 3.00	
	3	≥ 3.01 – 3.50	
	4	≥ 3.51	
college entrance examination paths	1	SNMPTN	Variable input
	2	SBMPTN	
	3	PPA	
	4	SPMU	
High School Origin	1	State	Variable input
	2	Private	
High School Major	1	Science	Variable input
	2	Social	
	3	Others	
Domicile	1	Bengkulu	Variable input
	2	Others	
Gender	1	Male	Variable input
	2	Female	
Scholarship	1	Yes	Variable input
	2	No	
Status	1	Single	Variable input
	2	Married	
Graduation rate	1	On time (≤ 4 year)	Variable target
	2	Late (>4 year)	
Graduation predicate	1	Cum laude	Variable target
	2	Very satisfactory	
	3	Satisfactory	

Figure 1: Attributes of data training.

4.4 Mining Process

The mining process is applied to create model that used for label of the new class. Through this research there are two classes formed, which are study duration and graduation predicate.

Decision tree is resulting the leaf that is containing opportunities of every class and attribute to be predicted as it seen in Figure 1. In further, the mining process is finding the entropy value, information gain, split information, and gain ratio in order to get the root node of the decision tree. To done those process, the computational can be seen in the equation 1 to 4. The root of the tree will be the highest value of the gain ratio. Later after root node is generated, internal node and leaf node is searched utilizing the same calculation as calculating the root node. Formed leaf nodes is containing the naïve bayes classifier. The result of the whole process that applying this hybrid decision tree and naïve bayes classifier is able to predict the duration rate of study and the graduation grade of the students.

4.5 Pattern Evaluation

Testing is done in this stage, which the performance of mining process is calculated. Confusion matrix is the method that is utilized for evaluate and validate the mining process. Confusion matrix contains amount of test record assembling on the table to predict the correctness or incorrectness (Renaningtias et al.,). The calculation performance model is based on the values of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). The form of the confusion matrix is shown in Figure 2.

Actual	Prediction	
	True	False
True	TP	FN
False	FP	TN

Figure 2: Table type styles.

Accuracy, precision and recall are calculated on the confusion matrix. The accuracy of the system on classify the data correctly is formulated utilizing the equation 8. For the amount of data that classified positively is calculated using equation 9. Then for the recall, it is presenting the percentage of positive category on the result of classification by the systems (see equation 10).

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{8}$$

$$precission = \frac{TP}{TP+FP} \tag{9}$$

$$recall = \frac{TP}{TP+FN} \tag{10}$$

5 RESULT AND DISCUSSION

The utilized data is the data that already completing the process of cleaning and transforming. As explained in the research procedure, the data cleansing is worked for erase insufficient data, then data transformation is for converting the data to the appropriate format. Mining process is done using hybrid decision tree and naïve bayes classification techniques to produce prediction for both graduation rate and graduation predicate of the students. Hence, as it shown in Table 1, are the attributes utilizing on this research.

5.1 Prediction of Graduation Rate

Class categories on this research to predict the study duration rate are on time and late. It is "on time" when students show they can graduate on 4 years. However, when its more than 4 years, it will be categorized as late.

Through this research, the performance of hybrid decision tree using C4.5 algorithm and naïve bayes classifier technique calculate according to arrangement of data partitions of 70%, 80%, and 90%. Its techniques is able to determine the most core attribute in the prediction process through the calculation of entropy (equation 2), ratio gain (equation 4), information gain (equation 1) and split information (equation 3). Then for the naïve bayes calculation it uses the equation 5 to 7. The whole result of prediction student rate of study duration is shown on the Figure 3 to Figure 6.

Partition	Class label 1	Class label 2
70%	150	65
80%	172	43
90%	193	22

Figure 3: Data partitions.

Partition	Gain Max	Code	Entropy	Info Gain	Split Info	Gain Ratio
70%	GPA 1	0	0	0.828	1.7911	0.046
		1	0.721			
		2	0.930			
		3	0.949			
		4	0.928			
80%	GPA 2	0	0	0.0864	0.1759	0.049
		1	0.979			
		2	0.998			
		3	0.936			
		4	0.337			
90%	GPA 1	0	0	0.0934	1.734	0.053
		1	0.650			
		2	0.907			
		3	0.967			
		4	0.872			

Figure 4: Attribute values of graduation rate.

In the Figure 3, it is seen that the 215 dataset is divided into 2 class labels with each class show the value of the class based on the partition values. C4.5 algorithm is implemented to work on the calculation of its partition, then it is resulting the value as it shows in Figure 4. There is a rule following the calculation on C4.5 algorithm, which its rules are describe in the Figure 5. When the rules are already formed, the existing probability on each rule then calculates utilizing the naïve bayes classifier algorithm. The result of the calculation is performed on the Figure 6.

	Rules of study rate duration
1	if (GPA_2==0) then > 4 years (id=1)
2	if (GPA_2==1) then > 4 years (id=2)
3	if (GPA_2==2 and entrance == PPA) then 4 years (id=4)
4	if (GPA_2==2 and entrance == snmptn) then > 4 years (id=5)
5	if (GPA_2==2 and entrance == spmu) then > 4 years
	(id=6)
6	if (GPA_2==3 and gender == male and major == science) then>4years(id=9)
7	if (GPA_2==3 and gender == male and major == social) then>4years(id=10)
8	if (GPA_2==3 and gender == male and major == others) then>4years(id=11)
9	if (GPA_2==3 and gender == female and ip_1==1) then>4years(id=13)
10	if (GPA_2==3 and gender == female and ip_1==3 and major==science) then 4 years (id=14)
11	if (GPA_2==3 and gender == female and ip_1==3major==soscial)then>4years(id=16)
12	if (GPA _2 == 3 and gender == female and ip_1 == 3 and major == social) then > 4 year (id = 17)
13	if (GPA _2 == 3 and gender == female and ip_1 == 3 and major == other) then > 4 year (id = 18)
14	if (GPA _2 == 3 and gender == female and ip_1 == 4) then > 4 year (id = 19)
15	if (GPA _2 == 4) then > 4 year (id = 20)

Figure 5: Prediction of graduation rate rules.

Partition	Accuracy	Precision	Recall
70%	60%	60.47%	74.29%
80%	65.12%	62.5%	86.96%
90%	72.73%	71.43%	83.33%

Figure 6: Confussion matrix of graduation rate.

5.2 Prediction of Graduation Predicate

There are three class categories for prediction graduation predicates, such as: cum laude, very satisfactory, and satisfactory. The steps of predicting the graduation predicate is as same as the process of prediction graduation rate.

First, the partition data is created into 70%, 80% and 90%. Then its partitioned data are calculated utilizing the equation 1 to 4, then it is resulting the values as presented on the Figure 7. After that, C4.5 and naïve bayes classifier are operated to result a prediction value (shown in Figure 9), based on the rules that created (shown in Figure 8).

Partition	Gain Max	Code	Entropy	Info Gain	Split Info	Gain Ratio
70%	GPA 1	0	0	0.1729	1.7911	0.0965
		1	0.353			
		2	0.515			
		3	0.757			
		4	0.947			
80%	GPA 2	0	0	0.707	0.1759	0.097
		1	0.235			
		2	0.305			
		3	0.499			
		4	0.617			
90%	GPA 1	0	0	0.1841	1.743	0.105
		1	0.206			
		2	0.305			
		3	0.499			
		4	0.617			

Figure 7: Attribute values of graduation rate.

	Rules of study grade prediction
1	if (GPA_2 == 0) then very satisfactory (id = 1)
2	if (GPA_2 == 1) then very satisfactory (id = 2)
3	if (GPA_2 == 2) then very satisfactory (id = 3)
4	if (GPA_2 == 3 and city == Bengkulu and scholarship == no and gender == male and GPA_1 == 1) then very satisfactory (id = 8)
5	if (GPA_2 == 3 and city == Bengkulu and scholarship == no and gender == male and GPA_1 == 2) then very satisfactory (id = 9)
6	if (GPA_2 == 3 and city == Bengkulu and scholarship == no and gender == male and GPA_1 == 3) then very satisfactory (id = 10)
7	if (GPA_2 == 3 and city == Bengkulu and scholarship == no and gender == male and GPA_1 == 4) then very satisfactory (id = 11)
8	if (GPA_2 == 3 and city == Bengkulu and scholarship == no and gender == female and GPA_1 == 1) then cum laude (id = 13)
9	if (GPA_2 == 3 and city == Bengkulu and scholarship == no and gender == female and GPA_1 == 2) then cum laude (id = 14)
10	if (GPA_2 == 3 and city == Bengkulu and scholarship == no and gender == female and GPA_1 == 3) then cum laude (id = 15)
11	if (GPA_2 == 3 and city == Bengkulu and scholarship == no and gender == female and GPA_1 == 4 and entrance == PPA) then very satisfactory (id = 17)
12	if (GPA_2 == 3 and city == Bengkulu and scholarship == no and gender == female and GPA_1 == and entrance == SNMPTN) then cum laude (id = 18)
13	if (GPA_2 == 3 and city == Bengkulu and scholarship == no and gender == female and GPA_1 == 4 and entrance == spmu) then cum laude (id = 19)
14	if (GPA_2 == 3 and city == Bengkulu and scholarship == ya) then very satisfactory (id = 20)
15	if (GPA_2 == 3 and city == other) then very satisfactory (id = 21)

Figure 8: Prediction of graduation grade.

Partition	Accuracy	Precision	Recall
70%	83.02%	66.67%	72.29%
80%	76.74%	67.5%	83.56%
90%	72.73%	73.43%	7.64%

Figure 9: Prediction of graduation grade.

From the examination result of prediction that is utilizing the confusion matrix, besides showing the accuracy value, it also presents the precision value and the recall value. Nevertheless, in the discussion of this research we are just focusing of the value of the accuracy since accuracy is the most important point of prediction.

As it shown on Figure 10, when we are comparing between the accuracy of prediction from graduation grade and graduation rate, we figure out that the higher value of partition the higher chance of the stability accuracy of the data is obtained. As the data partition is 70%, the difference percentage between result of graduation grade and rate prediction is 23.02%. It is reduced when the data partition is added 10% more, become 80%, the result shows that the range of difference is 11.02%. The difference evolves into 0% when the partition is 90%.

Moreover, with the stability of the result from predicting both graduation grade and graduation rate, then this method able to assist the management on the educational domain to make a better solution for implemented on the pedagogical process. Hence, the graduation target, both for quantity and quality of the graduate students able to be boosted in the better value.

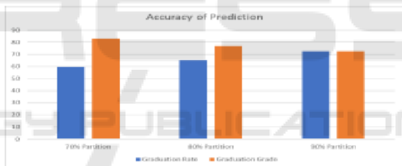

Figure 10: Comparisson of accuracy prediction

6 CONCLUSIONS

In this paper, we are presenting the utilization of the hybrid decision tree combined with the naïve bayes classifier. Our objectives on this research are all achieved. First, we are able to implementing the combination of naïve bayes with hybrid decision tree to make prediction of graduation grade and graduation rate. Which its result, the accuracy of prediction for graduation rate and graduation grade is 72.73% on the highest value partition, its 90%. Secondly, we are proved that, the higher value of the partition that applied on the collaboration hybrid decision tree and naïve bayes classification the higher consistency value of its accuracy gained.

REFERENCES

Belsis, P., Chalaris, I., Chalaris, M., Skourlas, C., and Tsolakidis, A. (2014). The analysis of the length of studies in higher education based on clustering and the extraction of association rules. *Procedia-Social and Behavioral Sciences*, 147:567–575.

Berland, M., Baker, R. S., and Blikstein, P. (2014). Educational data mining and learning analytics: Applications to constructionist research. *Technology, Knowledge and Learning*, 19(1-2):205–220.

Bhatia, P. (2019). *Data Mining and Data Warehousing: Principles and Practical Techniques*. Cambridge University Press.

Campagni, R., Merlini, D., Sprugnoli, R., and Verri, M. C. (2015). Data mining models for student careers. *Expert Systems with Applications*, 42(13):5508–5521.

Chalaris, M., Gritzalis, S., Maragoudakis, M., Sgouropoulou, C., and Tsolakidis, A. (2014). Improving quality of educational processes providing new knowledge using data mining techniques. *Procedia-Social and Behavioral Sciences*, 147:390–397.

Dutt, A., Aghabozrgi, S., Ismail, M. A. B., and Mahroeian, H. (2015). Clustering algorithms applied in educational data mining. *International Journal of Information and Electronics Engineering*, 5(2):112.

Farid, D. M., Zhang, L., Rahman, C. M., Hossain, M. A., and Strachan, R. (2014). Hybrid decision tree and naïve bayes classifiers for multi-class classification tasks. *Expert systems with applications*, 41(4):1937–1946.

Kaur, P., Singh, M., and Josan, G. S. (2015). Classification and prediction based data mining algorithms to predict slow learners in education sector. *Procedia Computer Science*, 57:500–508.

Lefebvre, W., Vurpillot, F., and Sauvage, X. (2016). *Atom Probe Tomography: Put Theory into Practice*. Academic Press.

Manjarres, A. V., Sandoval, L. G. M., and Suárez, M. S. (2018). Data mining techniques applied in educational environments: Literature review. *Digital Education Review*, (33):235–266.

Mayilvaganan, M. and Kalpanadevi, D. (2015). Cognitive skill analysis for students through problem solving based on data mining techniques. *Procedia Computer Science*, 47:62–75.

Mishra, T., Kumar, D., and Gupta, S. (2014). Mining students' data for prediction performance. In *2014 Fourth International Conference on Advanced Computing & Communication Technologies*, pages 255–262. IEEE.

Patarapichayatham, C., Kamata, A., and Kanjanawasee, S. (2012). Evaluation of model selection strategies for cross-level two-way differential item functioning analysis. *Educational and Psychological Measurement*, 72(1):44–51.

Pradeep, A., Das, S., and Kizhekkethottam, J. J. (2015). Students dropout factor prediction using edm techniques. In *2015 International Conference on Soft-Computing and Networks Security (ICSNS)*, pages 1–7. IEEE.

Renaningtias, N., Suseno, J. E., and Gernowo, R. Hybrid decision tree and naïve bayes classifier for predicting study period and predicate of student's graduation. *International Journal of Computer Applications*, 975:8887.

Shahiri, A. M., Husain, W., et al. (2015). A review on predicting student's performance using data mining techniques. *Procedia Computer Science*, 72:414–422.

Shukor, N., Tasir, Z., and van der Meijden, H. (2015). An examination of online learning effectiveness using data mining.

Sowmya, R. and Suneetha, K. (2017). Data mining with big data. In *2017 11th International Conference on Intelligent Systems and Control (ISCO)*, pages 246–250. IEEE.

Sundar, P. P. (2013). A comparative study for predicting students academic performance using bayesian network classifiers. *IOSR Journal of Engineering (IOSRJEN) e-ISSN*, pages 2250–3021.

Thai-Nghe, N., Drumond, L., Krohn-Grimberghe, A., and Schmidt-Thieme, L. (2010). Recommender system for predicting student performance. *Procedia Computer Science*, 1(2):2811–2819.