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ASSESSING AND FORECASTING ACADEMIC ACHIEVEMENT OF STUDENTS

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Abstract
Research in the fields of educational data mining (EDM) and learning analytics (LA) has become more intriguing since it reveals practical information from educational databases for a variety of uses, including forecasting students' progress. Predicting a student's performance can be useful for decisions in contemporary educational systems. While family expenditures and student personal information are frequently disregarded, existing techniques have employed aspects that are mostly connected to academic success and family financial assets. Learning analytics, discriminative classification models, and generative classification models are used to forecast a student's likelihood of successfully completing his degree.
Keywords: Educational data mining (EDM), Learning analytics (LA)

Introduction

Research in the fields of educational data mining (EDM) and learning analytics (LA) has become more intriguing since it reveals practical information from educational databases for a variety of uses, including forecasting students' progress. Predicting a student's performance can be useful for decisions in contemporary educational systems. While family expenditures and student personal information are frequently disregarded, existing techniques have employed aspects that are mostly connected to academic success and family financial assets.

It is essential to properly implement the appropriate pedagogical interventions to guarantee that students graduate on time and satisfactorily. This requires making accurate predictions about students' forthcoming performance founded on their continuing academic records. Although there is a wealth of research on forecasting student achievement when tackling issues or preparing for classes using data-driven techniques, predicting student performance when finishing degrees (such as college programmes) is considerably less explored and confronts unique challenges: (1) Backgrounds and course choices vary greatly across students; (2) Courses are not all equally useful for creating precise forecasts; (3) Student growth must be taken into account in the prediction.

The proposed system will comprise the tracking of detailed info of a student concerning his academic and curricular activity and would predict the right learning courses using an algorithm over the information tracked meeting the ambition or the goal for a student. In the last decade, school conducts examination manually. It has so many problems. The existing systems are very time consuming. It is difficult to analyse the exam manually. Results are not precise as calculation and evaluations are done manually. Result processing after summation of exam takes more time as it is done manually. So we introduce a Pre-school examination Portal system, which is fully computerized. Existing system is a large man power process and is difficult to implement. It provides an easy to use environment for both Test Conductors and Students appearing for Examination. In this study, a model for predicting student success in an academic organisation is provided. The method used is a machine learning approach known as a neural network. Furthermore, the significance of various attributes or qualities is studied in order to establish which of these are associated to student success.

It is essential to properly implement the appropriate pedagogical interventions to guarantee that students graduate on time and satisfactorily. This requires making accurate predictions about students' upcoming performance based on their continuing academic records. Predicting student success in finishing degrees (such as college programmes) is far less researched and presents additional obstacles, despite the fact that there is a wealth of literature on doing so:

1. Backgrounds and course choices vary greatly across students;
2. Courses are not all equally useful for creating precise forecasts;
3. Student growth must be taken into account in the prediction.

In this study, we create a cutting-edge machine learning technique for forecasting student success in degree programmes that can deal with these important issues. There are two key components to the suggested technique. For producing predictions based on students' changing performance states, first a bi-layered structure made up of several base predictors and a cascade of ensemble predictors is built. Second, a data-driven strategy based on probabilistic matrix factorization and latent component models is suggested to find course relevance, which is crucial for developing effective base predictors.

According to the provided studies, academic success of this is mostly based on their prior performance. Our analysis reveals that previous performance has a considerable impact on student achievement. Further, we established that the enactment of SVM increases with increases in dataset size. System will comprise the tracking of detailed information of a student regarding his academic and curricular activity and would predict the right learning courses using an algorithm over the information tracked meeting the ambition or the goal for a student. In the last decade, school conducts examination manually. It has so many problems. The existing systems are very time consuming. It is difficult to analyse the exam manually. Results are not precise as calculation and evaluations are done manually. Result processing after summation of exam takes more time as it is done manually. So we introduce a Pre-school examination Portal system, which is fully computerized. Existing system is a large man power process and is difficult to implement. It provides an easy to use environment for both Test Conductors and Students appearing for Examination. In this study, a model for predicting student success in an academic organisation is provided. The method used is a machine learning approach known as a neural network. Furthermore, the significance of various attributes or qualities is studied in order to establish which of these are associated to student success.

In view of the aforementioned obstacles, we present a unique strategy for forecasting student success in a degree programme in this work. We focus on predicting students' GPAs but the general framework can be used for other student performance prediction tasks. We make three major contributions.

1. We create a unique prediction system based on students' progressing performance phases. It has a bi-layered structure that includes a base predictor layer and an ensemble predictor layer. Multiple base predictors create local predictions in the base layer based on a snapshot of the student's current performance level in each academic term. An ensemble predictor in the ensemble layer forecasts the student's future performance by combining the outcomes of the local predictions and the previous-term ensemble prediction. The cascading of ensemble predictors over academic terms allows the prediction to incorporate students' developing progress while keeping complexity low. We also extract a guarantee of performance for our suggested method.
2. We develop a data-driven course clustering method based on probabilistic matrix factorization, which automatically outputs course clusters based on large, heterogeneous and sparse student course grade data. Base predictors are skilled using a variety of state-of-the-art machine learning techniques based on the discovered course clustering results. Specifically, only relevant courses in the same cluster are used as input to the base predictors. This not only reduces the training complexity but also removes irrelevant information and reduces noise in making the prediction.
3. e perform extensive simulation studies on an undergraduate student dataset collected over three years across 1169 students at the Mechanical and Aerospace Engineering department at UCLA. The results show that our proposed method is able to significantly outperform benchmark methods while preserving educational interpretability.

ARTIFICIAL NEURAL NETWORKS

Artificial Neural Network represents a set of input unites and output unites that are connected to each other by weighted connections. The ANN learns by changing the weights of the connections in a way so it is able to predict the right target label for some input data instances. One of the famous learning algorithms used to train the ANN is Backpropagation Algorithm. ANN has many advantages such as its high resistance to noisy datasets and its well performance on classifying patterns that has not been trained on so it's used in situations when there is a little knowledge of the relation between the class label and the features in the dataset. There are many real world applications of the ANNs such as image and handwritten recognition, speech recognition, laboratory medicine and pathology. There are many types of the ANNs which can be classified based on their architecture and design. One type is a fully connected multilayer feed forward ANN in which the network has an input layer, one or more hidden layers, and the output layer. Furthermore, its connections never return to an input unit or an output unit in the preceding tier. Furthermore, each unit in layer L supplies input to each unit in layer L+1. A three layer fully connected feed forward ANN has been used in this research. The network consists of an input layer, two hidden layers, and the output layer. The input layer has twenty input unites, neurons, while the first hidden layer has six hidden unites. The second hidden layer has three hidden unites. The fourth layer is the output layer which has only one output unite. The Rectifier Linear Unit has been used as the hidden unites' activation function.

RELATED WORK

In recent years, there has been a lot of interest in machine learning for education. A considerable portion of work focuses on predicting student performance in problem solving or course completion [10]. Many machine learning approaches have been used to construct prediction algorithms, including decision trees [11], artificial neural networks [12], matrix factorization [13], collaborative filters [14], and probabilistic graphical models [15][6]. Most of this work ignores the temporal/sequential effect that students improve their knowledge over time and treats the prediction as a one-time task. To account for the temporal/sequential effect, a three-mode tensor factorization (on student/problem/time) technique for predicting student performance in solving problems in ITSs was developed [16], and a similarity-based algorithm was proposed to issue predictions of student grades in courses only when a certain confidence level is reached [17]. These techniques, however, are not relevant in our environment due to the aforementioned significant discrepancies in forecasting student success in degree programmes. The ensemble learning approach, namely the Exponentially Weighted Average Forecaster (EWAF) [18], is used as a building component in our progressive prediction algorithm to enable progressive prediction of student performance and live update of the predictor as new student data is received. The main difference between an ensemble predictor and the traditional EWAF algorithm is that an ensemble predictor has access to multiple base predictors (experts) as well as the previous-term ensemble predictor, whose output summarises the outputs of all previous-term base predictors (experts), whereas the conventional EWAF algorithm has direct access to all experts. To the best of our knowledge, this is an unique architecture for developing predictors for gradually growing input spaces that decreases design and implementation complexity and scales readily with the number of academic words. In this setting, we prove that each ensemble predictor still performs asymptotically no worse than the best base predictor in hindsight among all previous-term base predictors in the worst case, thereby providing strong performance guarantee. More importantly, when the best base predictor is biased towards current-term base predictors, our algorithm is able to achieve better expected regret than the conventional method that has access to all experts directly and treats them equally.

COURSE RELEVANCE DISCOVERY

Our course relevance discovery technique is based on the latent component model [19] and performs course clustering using the probabilistic matrix factorization algorithm [20], both of which are widely used in recommender systems [21][22][23]. The problem that recommender systems face is similar to that of student performance prediction in that the dataset is sparse in the sense that each user has rated only a small set of items in the entire item space, whereas in our case, each student has taken only a small set of courses in the entire course space. The latent factor model is therefore used to discover the hidden latent factor that resolves the sparsity problem. Unlike recommender systems, which employ the identified latent factor to facilitate user similarity matching and item suggestions, our system leverages the discovered latent factor to cluster relevant courses. It is worth mentioning that sparse factor analysis is utilised in the learning context to evaluate a learner's understanding of the ideas underlying a domain and the linkages between a collection of questions and those concepts [24]. The authors of [25] draw a separate link between recommender systems and student performance prediction. They develop a collaborative filtering algorithm, which is used in recommender systems to recommend items to users based on user similarity. In this paper, we do not develop collaborative filtering prediction algorithms, although they can be adopted as base predictors in our method. More broadly, there is a rich literature on recommending relevant courses or problems to students based on their associated knowledge level, learning styles, and feedbacks [26] [27][28]. Course sequence recommendation, which considers the specific course constraints, was studied in [29]. To utilize logged data for course sequence recommendations and curriculum design, an off-policy estimator was developed to estimate how an unobserved policy performs given an observed policy [30]. A rank aggregation framework is adapted for the discovery of optimal course sequences at the university level [31]. However, whereas this literature aims to recommend courses/course sequences based on student backgrounds and past performance, the purpose of the current work is to predict future performance based on student backgrounds and past performance for a given curriculum.

METHODOLOGY

We present a unique strategy for developing predictors based on students' growing progress. The important point is that because predictor ft's input xti for term t is a superset of predictor ft's input xti1 for term t1, ft may capitalise on ft1's prediction output yi1 by adding the progressively additional information xti. This decreases the difficulty of building ft and makes the prediction algorithm scalable. Our approach to enable such progressive predictions is based on the ensemble learning technique and integrates offline learning and online learning. The proposed architecture consists of two layers — a base prediction layer and an ensemble prediction layer.

1. In the base prediction layer, we construct a set of base predictors H implemented using different prediction algorithms. For each base predictor h □H, let zh,it= h(θi,xti) denote the prediction result of h for student igiven the student's static feature and the current performance state xti. The base predictors are trained using a dataset consisting of all student data in the department without differentiating areas to maximally utilize the data. In fact, predictor h may even be trained differently for each term t's prediction task. Therefore, we write ht(θi,xti) rather than h(θi,xti). Learning the base predictors is done offline.
2. (2) In the ensemble prediction layer, we construct an ensemble predictor for each term. The ensemble predictor ftfor term t synthesizes the previous ensemble output yˆit−1 and output of the base predictors zh,it,□h □Htand makes a final prediction yˆitbased on yˆit−1 and zh,it,□h □Ht. Because students from various places take different courses and in different sequences, the temporal correlation is likely to be variable, the ensemble predictor is trained using student data from the same area. The ensemble predictors are learned online.
3. A system block diagram of the proposed bi-layered architecture for the term t ensemble learning is illustrated in Figure. Although the proposed architecture is easy to understand, a couple of challenges must be addressed in order to achieve good prediction performance. The first challenge is how to construct the base predictors. Although existing off-the-shelf machine learning algorithms can be used to perform the prediction task, we would like to construct a base predictor that is customized to the considered course grade prediction problem to improve its prediction performance. A specific consideration in this regard is what information should be included in the training of the predictor as well as making the prediction. The second challenge is how to construct the ensemble predictors and take the temporal correlation into account. Specifically, this is to answer how to synthesize the prediction results of the multiple base predictors as well as the prediction from the previous term.

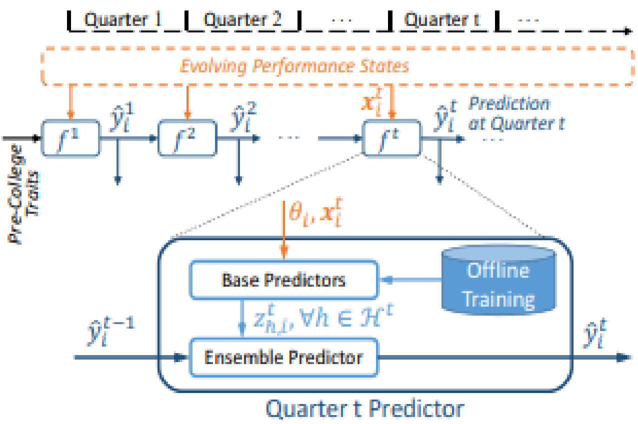


Figure 1: System Block Diagram.

Method Overview

An important question when training htis how to construct the (input) feature vector given the student performance states x . Because students come from different areas as well as have different interests, the courses in the performance states can be very different. A straightforward way is to construct a large feature vector that contains the grade of courses that have appeared in Dt. Entries corresponding to courses that a student did not take in this vector are filled with null values. In this way, students have the same feature vector format. However, there are two major drawbacks for this method. First, the feature vector can be very large, especially in the later terms of the program when students have taken more courses. The problem is more severe since even though students in different areas may have many courses in common, they also have considerably many distinct courses. In addition to the increased complexity, the second drawback is the possible degraded prediction accuracy due to added noise since not all courses, even the courses within the same area, have predictive power for predicting the grade of the targeted course. Therefore, we will learn the set of courses that are more relevant to the targeted course. Notice that for different targeted courses, the relevant courses will also be different. Once the relevant courses are found, the feature vector is constructed using only elements in xtithat corresponds to the relevant courses. Then our method will utilize various state-of-the-art supervised learning algorithms to train the base predictors. In this paper, we do not invent new supervised learning algorithms but only focus on learning the relevant courses.

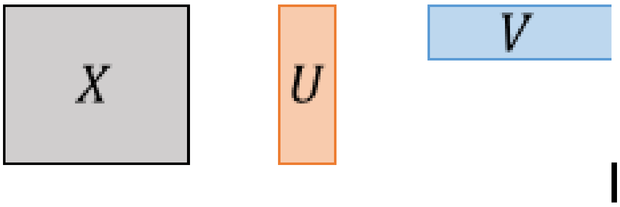
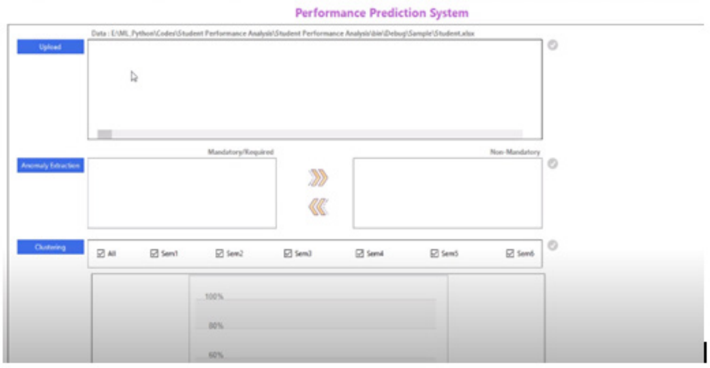


Figure 2: Illustration of matrix factorization.

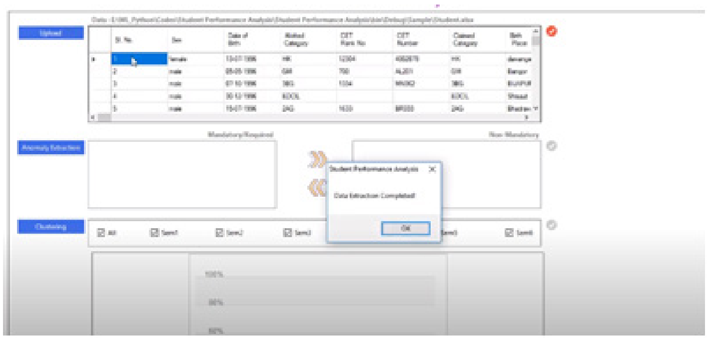
RESULTS



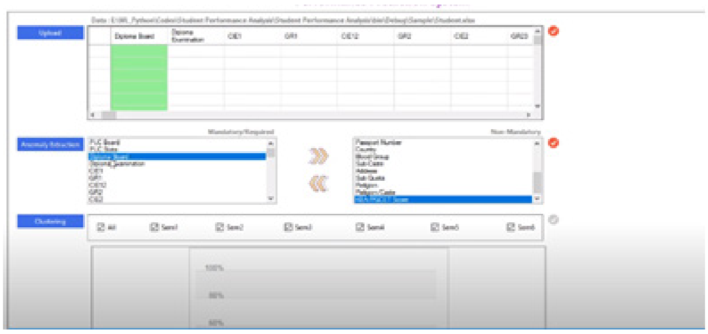
User interface of the performance Prediction System

gender	NationalIT	PlaceofBir	StageID	GradeID	SectionID	Topic	Semester	Relation	raisedhan	VisITedRe	Announce	Discussio	ParentAn	Parentsch	StudentAl	Class
M	KW	KuwaIT	lowerleve	G-04	A	IT	F	Father	15	16	2	20	Yes	Good	Under-7	M
M	KW	KuwaIT	lowerleve	G-04	A	IT	F	Father	20	20	3	25	Yes	Good	Under-7	M
M	KW	KuwaIT	lowerleve	G-04	A	IT	F	Father	10	7	0	30	No	Bad	Above-7	L
M	KW	KuwaIT	lowerleve	G-04	A	IT	F	Father	30	25	5	35	No	Bad	Above-7	L
M	KW	KuwaIT	lowerleve	G-04	A	IT	F	Father	40	50	12	50	No	Bad	Above-7	M
F	KW	KuwaIT	lowerleve	G-04	A	IT	F	Father	42	30	13	70	Yes	Bad	Above-7	M
M	KW	KuwaIT	MiddleScl	G-07	A	Math	F	Father	35	12	0	17	No	Bad	Above-7	L
M	KW	KuwaIT	MiddleScl	G-07	A	Math	F	Father	50	10	15	22	Yes	Good	Under-7	M
F	KW	KuwaIT	MiddleScl	G-07	A	Math	F	Father	12	21	16	50	Yes	Good	Under-7	M
F	KW	KuwaIT	MiddleScl	G-07	B	IT	F	Father	70	80	25	70	Yes	Good	Under-7	M
M	KW	KuwaIT	MiddleScl	G-07	A	Math	F	Father	50	88	30	80	Yes	Good	Under-7	H
M	KW	KuwaIT	MiddleScl	G-07	B	Math	F	Father	19	6	19	12	Yes	Good	Under-7	M
M	KW	KuwaIT	lowerleve	G-04	A	IT	F	Father	5	1	0	11	No	Bad	Above-7	L
M	lebanon	lebanon	MiddleScl	G-08	A	Math	F	Father	20	14	12	19	No	Bad	Above-7	L
F	KW	KuwaIT	MiddleScl	G-08	A	Math	F	Mum	62	70	44	60	No	Bad	Above-7	H
F	KW	KuwaIT	MiddleScl	G-06	A	IT	F	Father	30	40	22	66	Yes	Good	Under-7	M
M	KW	KuwaIT	MiddleScl	G-07	B	IT	F	Father	36	30	20	80	No	Bad	Above-7	M
M	KW	KuwaIT	MiddleScl	G-07	A	Math	F	Father	55	13	35	90	No	Bad	Above-7	M
F	KW	KuwaIT	MiddleScl	G-07	A	IT	F	Mum	69	15	36	96	Yes	Good	Under-7	M
M	KW	KuwaIT	MiddleScl	G-07	B	IT	F	Mum	70	50	40	99	Yes	Good	Under-7	H
F	KW	KuwaIT	MiddleScl	G-07	A	IT	F	Father	60	60	33	90	No	Bad	Above-7	M

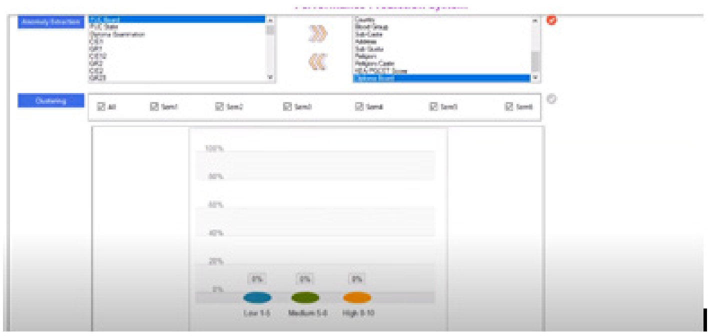
Dataset used for the work



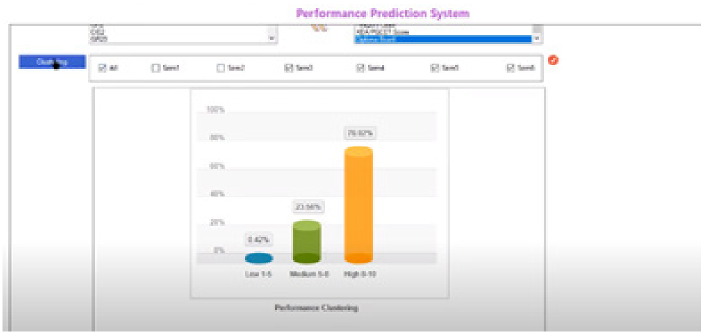
Data Extraction Process



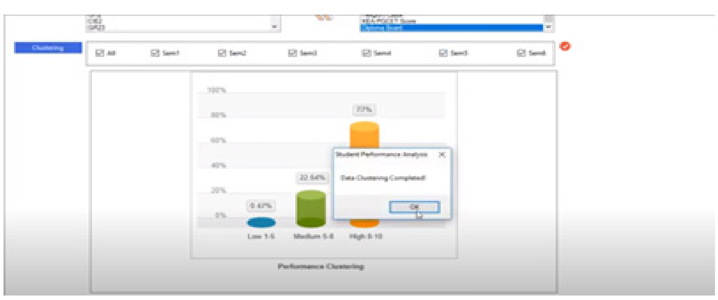
Data extraction



Data Clustering Process

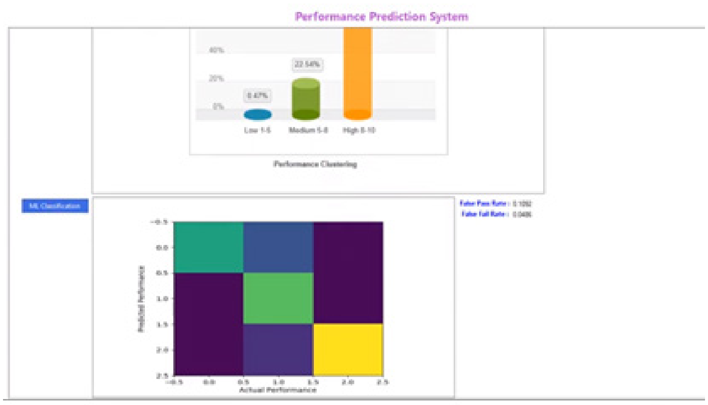


Performance Clustering



Data clustering Completed

Machine Learning Classification



CONCLUSION

According to current research, pupils' academic achievement is mostly determined by their prior performance. Our analysis reveals that previous performance has a considerable impact on pupils' performance. Furthermore, we verified that the performance of neural networks improves as dataset size grows. According to current studies, earlier performance has the greatest influence on students' academic attainment. According to our findings, prior performance has a significant influence on students' performance. Furthermore, we demonstrated that the performance of neural networks increases with increasing dataset size. In the future, applications similar to the one developed, as well as any improvements thereof may become an integrated part of every academic institution. This project can be used in any organization, college as analysis purpose. A latent factor model-based course clustering method was developed to discover relevant courses for constructing base predictors. An ensemble-based progressive prediction architecture was developed to incorporate students' evolving performance into the prediction. These data-driven methods can be used in conjunction with other pedagogical methods for evaluating students' performance and provide valuable information for academic advisors to recommend subsequent courses to students and carry out pedagogical intervention measures if necessary. Additionally, this work will also impact curriculum design in degree programs and education policy design in general. Future work includes extending the performance prediction to elective courses and using the prediction results to recommend courses to students.

REFERENCES

[1] H. Cen, K. Koedinger, and B. Junker, Learning factors analysis a general method for cognitive model evaluation and improvement, in International Conference on Intelligent Tutoring Systems, Springer, 2006, pp. 164175

[2] Ravi TejaYarlagadda, "THE RPA AND AI AUTOMATION", International Journal of Creative Research Thoughts (IJCRT), ISSN:2320-2882, Volume.6, Issue 3, pp.365-373, September 2018, Available at: http://www.ijcrt.org/papers/IJCRT1133933.pdf

[3] IshaqAzhar Mohammed. (2013). Intelligent authentication for identity and access management: a review paper. International Journal of Managment, IT and Engineering (IJMIE), 3(1), 696–705. Retrieved from https://www.ijmra.us/project doc/IJMIE_JANUARY2013/IJMIEJan13Ishaq.pdf

[4] M. Feng, N. Heffernan, and K. Koedinger, Addressing the assessment challenge with an online system that tutors as it assesses, User Modelling and User-Adapted Interaction, vol. 19, no. 3, pp. 243266, 2009.

[5] J. Xu, K. H. Moon and M. van der Schaar, "A Machine Learning Approach for Tracking and Predicting Student Performance in Degree Programs," in IEEE Journal of Selected Topics in Signal Processing, vol. 11, no. 5, pp. 742-753, Aug. 2017, doi: 10.1109/JSTSP.2017.2692560.

[6] Altabrawee, Hussein & Ali, Osama &Qaisar, Samir. (2019). Predicting Students' Performance Using Machine Learning Techniques. JOURNAL OF UNIVERSITY OF BABYLON for pure and applied sciences. 27. 194-205. 10.29196/jubpas.v27i1.2108.

[7] Rupali, Bagal&Matele, Ramdas&Machhindra, Bhavika& Kailas, Wable& Mohammad, Sameer. (2019). Tracking and Predicting Student Performance Using Machine Learning. SSRN Electronic Journal. 6. 439-442.

[8] HashmiaHamsa, Simi Indiradevi, Jubilant J. Kizhakkethottam, Student Academic Performance Prediction Model Using Decision Tree and Fuzzy Genetic Algorithm, Procedia Technology, Volume 25, 2016, Pages 326-332, ISSN 2212-0173, https://doi.org/10.1016/j.protcy.2016.08.114.

[9] Mustafa Agaoglu, "Predicting Instructor Performance Using Data Mining Techniques in HigherEducation," IEEE Access , Volume: 4 ,2016.

[10] [2] TriptiMishra,Dr. DharminderKumar,Dr. SangeetaGupta,"Mining Students' Data for Performance Prediction," in fourth International Conference on Advanced Computing & Communication Technologies,2014.

[11] Keno C. Piad, Menchita Dumlao, Melvin A. Ballera, Shaneth C. Ambat," Predicting IT Employability

Using Data Mining Techniques," in third International Conference on Digital Information Processing, Data Mining, and Wireless Communications (DIPDMWC), 2016.

[12] BipinBihariJayasingh,"A Data Mining Approach to Inquiry Based Inductive Learning Practice In Engineering Education," in IEEE 6th International Conference on Advanced Computing, 2016.

[13] S. M. Merchán,"Analysis of Data Mining Techniques for Constructing a Predictive Model for Academic,"IEEE Latin America Transactions, vol. 14, no. 6, June 2016.

[14] KonstantinaChrysafiadi and Maria Virvou," Fuzzy Logic for adaptive instruction in an e-learning environment for computer programming," IEEE Transactions on Fuzzy Systems, Volume: 23, Issue: 1, Feb. 2015.

[15] M. Mayilvaganan,D. Kalpanadevi ," Comparison of Classification Techniques for predicting the performance of Students Academic Environment," in International Conference on Communication and Network Technologies (ICCNT), 2014.

[16] Crist´obal Romero," Educational Data Mining: A Review of the State of the Art," IEEE Transactions On Systems, Man, And Cybernetics—Part C: Applications And Reviews, Vol. 40, No. 6, November 2010.

[17] Kuzilek, J.; Hlosta, M.; Herrmannova, D.; Zdrahal, Z.; Wolff, A. OU Analyse: Analysing at-risk students at The Open University. Learn. Anal. Rev. 2015, 2015, 1–16

[18] Kovacic, Z. Early Prediction of Student Success: Mining Students' Enrolment Data. In Proceedings of the Informing Science and Information Technology Education Joint Conference, Cassino, Italy, 19–24 June 2010.

[19] Watson, C.; Li, F.W.; Godwin, J.L. Predicting performance in an introductory programming course by logging and analyzing student programming behavior. In Proceedings of the IEEE 13th International Conference on Advanced Learning Technologies, Beijing, China, 15–18 July 2013; pp. 319–323.

[20] The White House, "Making college affordable," https:// www.whitehouse.gov/issues/education/higher-education/ making-college-affordable, 2016.