Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.98549519

COLLEGE STUDENT PERFORMANCE DETECTION USING MACHINE LEARNING WITH DSS

Mr.C.John Paul
Ph.D Research scholar, Bharathiar University, Coimbatore -641046
E-Mail : jpcalling@gmail.com

Dr.K.Geetha
Assistant Professor, Department of Computer Science, Bharathiar University, Coimbatore -641046 E-Mail : geethakab@gmail.com

Abstract:
The primary goal of any educational institution is to provide students with the best possible education and skills. To achieve this objective, it is necessary to identify students who require additional assistance and take effective steps to improve their academic performance. To produce optimal outcomes and reduce the risk of failure, educational programs need innovative methods of enhancing school efficiency. The Educational Decision Support System (EDSS) has recently gained popularity in the education system, as it enables continuous monitoring and assessment of student outcomes. However, inadequate information systems face difficulties and obstacles in utilizing EDSS to its full potential due to imprecise data, insufficient characterization, and inadequate databases. Therefore, a comprehensive literature review and selection of the most accurate predictive methodology are critical to improve the prediction process. In this study, machine learning methods were employed to construct a classifier that can predict students' success in the economic field. This paper proposes a knowledge base DSS model that utilizes machine learning techniques to evaluate student performance based on their mid-term and final-term exam results.

Keywords: DSS, Artificial Neural Network, SVM, ML, Regression

1. INTRODUCTION

Improving student success and raising the standard of education across all institutions is crucial. To achieve this goal, it is essential to conduct a comprehensive study of students' prior academic history. The Educational Decision Support System (EDSS) is an effective tool for predicting student outcomes and optimizing their educational experience. By analyzing student data and identifying their needs, we can enhance the success rate of students in both mid and final stages of their education. EDSS collects important characteristics and past academic records of students to evaluate their performance and estimate their future outcomes. To gain a better understanding of student performance, various machine learning methods and classification algorithms are applied. The ultimate aim of EDSS is to reduce failure rates, create a better learning environment, and assess the core features that contribute to student achievement. Predictive models are developed to forecast results and improve students' performance, while also providing insights for the academic process in the upcoming year.

Different types of machine learning algorithms, including Naïve Bayes, decision trees, neural networks, and statistical methods, have been used in recent years to extract relevant information from student data. These approaches help support decision-making systems, detect outliers, and identify trends. While academic achievement is usually calculated using past exam scores, there are other significant attributes that can influence a student's overall performance. Recent research on student databases has focused on various methodological and statistical experiments. Kabakchieva and colleagues have used Bayes and decision-making classifications to predict student success based on pre-university results. Other approaches have utilized neural networks, computational models, and ID3 protocols. By leveraging EDSS and the latest machine learning techniques, we can enhance student success and improve the overall quality of education.

2. RELATED WORKS

There is a vast amount of research available on using machine learning methods to estimate student success and improve education in the modern world. Osmanbegović and his collaborators in projects [2, 3] have compared various data mining methods, including the Bayesian Classification Network and decision-making algorithms, with neural networks for classification. Their work has focused on datasets from Tuzla students and economic personnel between 2010 and 2011, using the Weka program to analyze the data. The results showed that MLP, NB, and J48 algorithms were effective in predicting student success, but further testing is necessary to ensure reliability and consistency. However, this study did not take into account students' backgrounds and characteristics. Marquez-Vera and his colleagues, as well as Sergi Rovira [4, 5], proposed a system that employed real figures from 670 Zacatecas students in Mexico and Barcelona University results. They used a white-box classification system, algorithms for decision trees, and inference rules to detect loss ratios and school dropout rates. Three studies were performed to collect features that could predict success, and they found that only 15 of the 77 qualities deemed important for student success were effective predictors. Overall, machine learning methods offer great potential for estimating student success and improving education. Further research is needed to fully understand the complexities of student success and how to best apply machine learning techniques to optimize it.The use of dimensional simulation and computational techniques has allowed researchers to evaluate the effectiveness of various education systems. The Weka Tool has been utilized in several studies, including Kabakchieva et al.'s work on predicting student success based on previous college and individual qualities using data mining algorithms. Two rules for learning were employed, the decision-taker and next neighboring categories, with reliable and excellent performance seen using Weka filters in J48 and JRip data sets. However, kNN and Bayes classification systems did not work. Ahmed et al. suggested using ID3 as a separate approach to predict student results, ranking methods, clustering, artificial intelligence, neural networks, regression, related rules, generics, and decision trees. In their study, 1547 documents were compiled for success estimation, and Weka was used for decision tree implementation. However, characteristics such as attendance, temperament, and environmental conditions were not monitored. Tamhane et al. used longitudinal information from the Gwinnett County Public Schools to evaluate strategies for implementing missed principles, including imputation of means, logistic regression, decision-making trees, and the naive Bayes. Logistic regression offered the best outcomes, but the process of filling missed values made predictions noisy, and a single classification was not enough to provide the student's optimum risk predictions. The behavioral details and causes of registration should also be taken into consideration. Arora et al. used a neural network approach to forecast student marks, mapping Gaussian method based on a radial equation for inputs. They used knowledge related to grade details for students between 2010 and 2011 and 2011 to predict current marks. However, the specifications of the projection were not enough to estimate results for the next years, and there was no definition of a proper algorithm and functional execution. Ktona et al. proposed using data mining techniques to allow students to break into clusters for academic success using c4.5 and k means algorithms for classification rules and clustering. Lime survey was used, but the small number of participants made the platform ineffective. Christian et al. used the NB tree classification model to estimate student success. Overall, there have been several approaches to predict student success, but the effectiveness of these methods varies. Characteristics such as attendance and environmental conditions should be taken into account to provide better risk predictions.The datasets contain various information, including scholarly, educational, enrollment, and personal details related to students' studies. To develop a classification model for evaluating student achievement, the Weka data mining toolkit is utilized. Gender, GPA, credit, and assessment score are significant features used in the model. Using data sets from higher education institutions is a more effective way to obtain insights into students' academic performance. Artificial intelligence methods are also employed to enhance the outcomes[6,7]. Grivokostopoulou and colleagues use semantic rules to track students' learning progress and devise their results. Semantic laws and ontologies are also used to improve schooling and yield benefits. Several artificial intelligence techniques are utilized for adaptive learning, including the powerful decision tree technique, c4.5 and card, which react to AI lost or passed percentages beforehand. Weka is used for tests. However, the study does not examine gender efficiency laws or errors in research, and missing data is not managed correctly. In Wang and colleagues' study, a basic model of linear regression is used to estimate accumulated GPA, which is a modern approach that uses mobile latent detecting to deduce research and social activity. The Dartmouth College students' data sets are used, and pitch and breakpoints are used to demonstrate trends, minimize absolute declines, and use the operator as a predictive model. This method is effective, as no study has been conducted by using passive sensor data and smartphone time series analyses as indicators. To predict students' performance, the indicator of longitude of their life, style, and behavior is used. Data from Washington State University are available for the course to be predicted. Based on observational analysis, Carters and colleagues suggest a normalized programming state model, which is unattainable in beginner programming environments. The learner's online social activity has an impact on the predictive ability of the standardized state scheduling algorithm. The study specifies the programming skills and learning work of Carter and colleagues, ignoring other research to forecast results.

Mgala and colleagues [24] proposed a thesis centered on developing a computer-based prediction method. Their model utilized a broad dataset consisting of 2426 graduates who had taken the Kenya primary school exam diploma. To handle missing values, the average fee was used in the preprocessing stage. The feature selection technology, machine learning techniques, and data mining algorithms were employed in constructing the prediction model. Logistic regression, multilayer perceptron, minimum optimization sequentially algorithm, Bayesian network classification schemes, naïve Bayes classificatory, random forest classification, and J48 algorithms were utilized. The datasets used were based on rural variables, and the model was not expected to yield efficient results for urban education systems, college, or university students. Personal descriptions of students and familial spending data were considered to be very useful in predicting their performance [8]. Classification was deemed to be a viable option for predicting the student's optimal risk. The neural network approach was used by Arora and colleagues [17] to forecast student marks. Inputs for mapping the Gaussian method were based on a radial equation. Knowledge about grade details for students between 2010 and 2011 and 2011 was used to predict the current marks. The record included over a thousand student details, with around two hundred and fifty subjects.

3. MACHINE LEARNING

In this section, a brief overview of the machine learning methods used in the study is provided. Machine learning has endowed computer systems with new skills. To train machine learning models, data from various sources, also known as training data, was acquired. The effectiveness of the model depends on the quality and quantity of the data used. To prepare the data for machine learning training, it is necessary to clean and randomize the data and create simulations of the relationships between the concentrations [27]. Machine learning algorithms possess the strength to predict responses automatically, surpassing human evaluations and creating more powerful models based on this automated learning process.

3.1 Artificial Neural Networks

The Artificial Neural Network (ANN) is a set of interconnections between input and output units that work together to predict the correct label for certain input cases. ANN learns through adjusting the weight of connections between the units, using well-known learning algorithms such as the Back-propagation algorithm. With its high tolerance for noisy data and efficient classification designs, ANN is often utilized in cases where the relationship between the class mark and the data set is unknown.

3.2 Logistic Regression

Logistic regression offers a mathematical modeling mechanism that illustrates the relationship between multiple explanatory variables, X1...XK, and a dependent variable, D. The logistic model utilizes the logistic function as a statistical structure that maps input values onto a scale of 0 to 1. This model estimates the likelihood of an occurrence, which is bounded between approximately 0 and 1[8,9].

3.3 Naïve Bayes

The Naïve Bayes classification paradigm is considered the simplest form of Bayesian modeling[9,10]. This model assumes that each attribute of the function is independent of other attributes given the class label. For each instance x in the dataset with attributes a1, a2,... ai, the function F(x) corresponds to any value in a predetermined set V = (v1, v2, ... vj).

3.4 Decision tree

Decision trees have found practical applications in various fields, including finance, surgery, molecular biology, image processing, and astronomy[10,11]. To construct a decision tree, a selection measure is required to choose the most informative attributes or functions and split the training instances into distinct target groups. Common metrics used for this purpose include information gain, profit ratio, and Gini index. Some popular decision tree algorithms include ID3, CART, and C4.5.

4. ANALYTCS OF EDUCATION

4.1 Support System

When we acknowledge education as one of the most pressing global issues, it becomes apparent that decision-making is a crucial responsibility for managers. They must gather and analyze relevant information about management problems in order to choose appropriate courses of action. Higher education administrators must also understand the decision-making process, as the education industry, like all regulated entities, operates within a decision-making framework. Decision-making in all sectors can be complicated by factors such as complex situations, information overload, data transmission within the organization, risk, and unstable conditions[12,13]. To address these challenges, educational institutions must equip themselves with effective tools and resources to support persuasive decision-making within any management framework. While information systems have long included decision-making support modules, the broader context requires additional funding and administrative data analysis. One approach to implementing a decision support system (DSS) in higher education is to develop valid conceptual and academic instruments for collecting, organizing, and analyzing crucial data and knowledge to facilitate the decision-making process.

4.2 Knowledge Management

Educational knowledge management is the dynamic system of components, processes, and relationships that exist between human capital, facilities, technologies, information, and knowledge staff. These partnerships operate within an "environment" that can either encourage or hinder information management behavior[14]. The prevalent approach to studying organizational knowledge management is a systematic and evidence-based methodology that focuses on information and technology. This systemic methodology simultaneously explores and studies the cultural influences within the enterprise and knowledge management system, including humanist, technostructural, and awareness and environment factors[15,16]. A formal description of knowledge management is necessary to fully understand its complexity. Generally, knowledge management refers to an integrated, regular, targeted, and ongoing socio-technical function that aims to promote, capture, gain, generate, organize, store, retrieve, share, distribute, transfer, reuse, and evaluate experiences, knowledge, and assets (both tacit and explicit) in order to achieve competitive advantage by improving the quality of knowledge and knowledge management practices.

4.3 Dialog management

Advancements in graphics, interaction styles, software tools, dialog systems, language translation software, and "widgets" have significantly impacted the field of computer-human interaction. Graphical user interfaces (GUIs) played a critical role in facilitating the creation of realistic interaction designs for computers. Dialog refers to the act of communicating or talking and is considered a fundamental human skill. It can serve as an end in itself, as a means of education, or as a platform for the co-construction of new ideas and definitions. Dialog encompasses not only verbal communication but also nonverbal and multimodal interactions. While dialog has the potential to serve as a tool for education and growth, it can also be limited by logistical and political factors such as educational frameworks, curriculum, and appraisal systems[18].

4.4 Decision Management

The decision-making process is widely regarded as the most crucial aspect of effective management. In many fields, policy-making challenges, such as curriculum administration, are prevalent. When it comes to educational issues, a significant portion of decisions is based on rudimentary knowledge or intuitive perspectives. The decision-making mechanism involves selecting from a range of options to achieve the desired outcome.

4.5 Expert System

An expert system is a type of software that aims to emulate human behavior in a particular field. By utilizing a knowledge base derived from human experts, it can resolve issues or provide explanations in situations where one would typically consult with one or more human experts. These systems are specifically designed to address complex topics that typically require human ingenuity and expertise. Therefore, expert systems are based on the knowledge and skills of human specialists or experts[19,20].

4.5.1 User Interface

Users interact with the system through an integrated interface, through which they generate requests on specific topics. The system then processes the request and provides a response or guidance on the question. The distinctive features of this interface allow clients to inquire about the methodology, rationale, and formatting of the system's responses[21,22].

4.5.2 Knowledge base

Expert analysis and evidence gathering are necessary for developing a knowledge base in areas where there is a shortage of expertise. As the system evolves, new regulations can be introduced and outdated ones can be removed using the acquisition module to update the knowledge base. These updates account for technological advancements, inventions, developments, and discoveries that lead to improvements in the field[24,25].

4.5.3 An inference engine

The system functions like a search engine that retrieves data from the knowledge base based on the customer's query. The deduction engine utilizes the user's question to search the knowledge base and provide a relevant response or advice.

4.5.4 Knowledge engineering

Knowledge engineering is a field within computer science that involves developing and implementing artificial intelligence systems. The Domain Expertise Province focuses on the expertise within a specific mission area. This domain knowledge encompasses both systematic knowledge found in textbooks and experiential information gained through expertise.

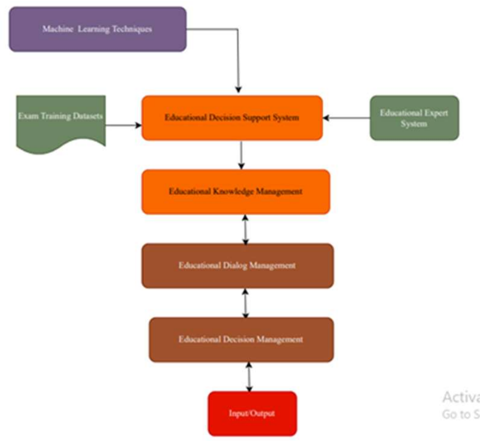

Figure 1 Educational Knowledge base

5. DATA SET

The proposed model is built using a new dataset. Table 1 provides a description of the dataset. It contains 268 instances of data on economics students, both those who took internal test (IT) and semester test (ST) exams (Type A), as well as exams related to their courses. The data includes the number of questions, correct and wrong answers, and the resulting scores. This dataset is used for training the model.

S.No	Features	Description
1	UID	Student Unique Identification (Roll No)
2	Name	Name of student
3	Gender	Male, Female
4	Course	Course ID
5	Subject	Subject name and subject code
6	Exam duration	Mid-term (MT), Final-term (FT)
7	Question	Number of Question
8	Correct	Correct answer
9	Wrong	Wrong answer
10	Total score	Gain percentage
11	Psychometric Factor	To evaluate the exam stresses

Table 1 Description of Data Sets

The following are the parameters based on algorithms:

a. Accuracy: describes the correctness of value

b. Probability Threshold: Presents the True Positive and True Negative rates.

c. Execution Time: Time of running the algorithm on dataset.

d. Precision: (number of true positive)/(number of true positive +False positives)

e. Recall: [(number of true positive)/(number of true positive/ number of false negatives)]

f. Number/Size of Rules

g. ROC Area: (Receiver operating characteristics) used alternative to accuracy [12].

h. F-measures: 2*[(precision*recall)/(precision + recall)]

i. Geometric Mean

6. EXPERMENTAL AND DISCUSSION

6.1 Flowchart of Students Performance

Predicting academic success in students can provide valuable insights into their ability to conduct research and perform well in their academic pursuits. This approach can offer informed instruction, personalized recommendations, and early interventions to enhance their learning experience and educational satisfaction. Furthermore, it can identify students who are at risk of underperforming, leading to interventions that can improve their exam results. A successful and reliable predictive model can be used to define optimal student curriculum paths and even replace structured exams, thereby reducing the test burden and workload that negatively affect both teachers and students. Additionally, learning success prediction can assist universities in selecting the best candidates from a pool of newcomers. Quality estimation can also be used to provide more knowledgeable instruction and make informed decisions for classes, courses, and individual courses, thus optimizing the ability of students to succeed and minimizing the likelihood of errors that could impact education encouragement at all levels. Overall, predicting academic success in students is a valuable tool that can enhance their learning experience, improve educational outcomes, and benefit both students and teachers.

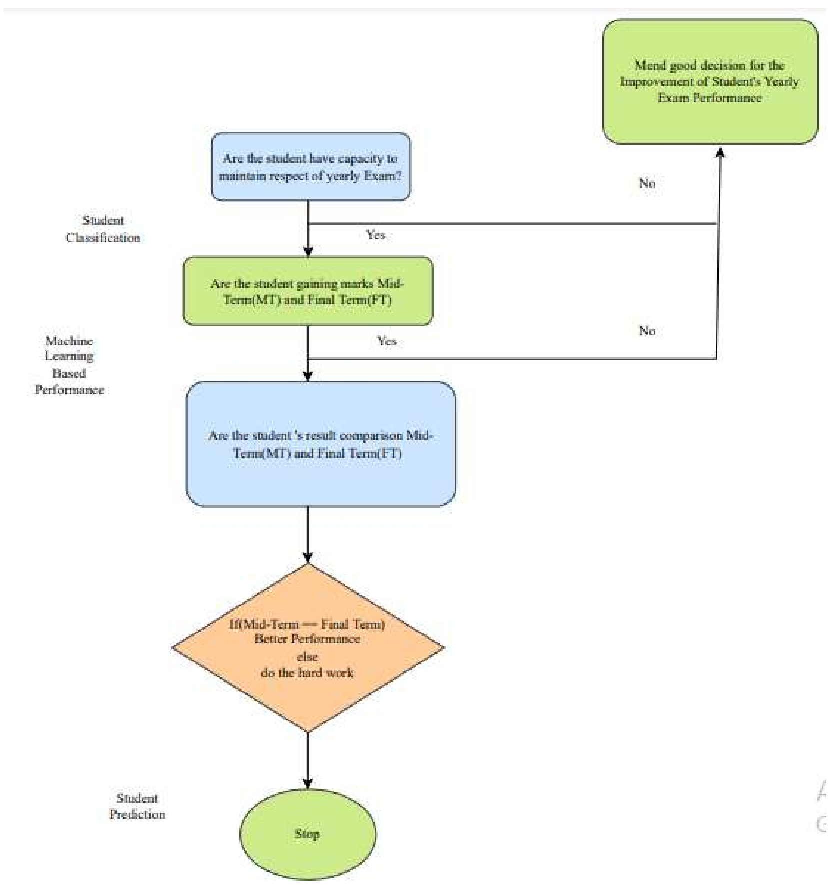

Figure 2 Flow chart Student Performance

6.2 Sample Data

A classifier has been developed using machine learning techniques to forecast the academic performance of students taking an economics course at Table 2 displays the training dataset containing information on ten students. The input data for the classifier is sourced from a CSV file that includes details such as student ID, gender, course, exam type, scoring percentage marks, and marks from the internal and semester exams. All the input data is in alphanumeric format. Table 2 presents the sample input data.

Course	Exam	ID	Correct	Wrong	Score
Course-1	Semester	20211485	45	5	90
Course-2	Semester	20211548	32	18	64
Course-3	Semester	20215248	45	5	90
Course-4	Semester	20212578	42	8	84
Course-5	Semester	20218426	48	12	96
Course-6	Semester	20212587	18	32	36
Course-7	Semester	20219632	25	25	50
Course-8	Semester	20211478	18	32	36
Course-9	Internal	20212648	28	22	56
Course-10	Internal	20212654	35	15	70
Course-11	Internal	20212354	34	16	68
Course-12	Internal	20212684	42	8	84

Table 2 Sample of Data Sets

6.3 Analysis

The primary objective of our study was to predict the performance of students in internal and semester exams. To achieve this, we utilized a test dataset comprising 268 records of final-term exams and 268 records of internal exams. Our analysis revealed that out of these 536 students, 68 had a likelihood of scoring similarly in both exams, while 100 had a higher probability of performing better in internal exams than in semester exams. Conversely, the remaining students had a greater chance of achieving better results in the semester exams than in the internal exams. Our analysis involved the evaluation of 25 questions attempted by each student, with correct answers used to calculate the overall percentage. Upon examination of the results, we observed that some students performed better in internal exams than in semester exams. Specifically, Student 1 and Student 2 demonstrated superior performance in internal exams, while Student 3 and Student 4 excelled in the semester exams. Meanwhile, Student 5 scored equally in both exams. These findings suggest that some students may be more confident in internal exams, while others may be more comfortable with semester exams. Additionally, some students consistently performed well across both exams and worked hard to improve their academic performance.

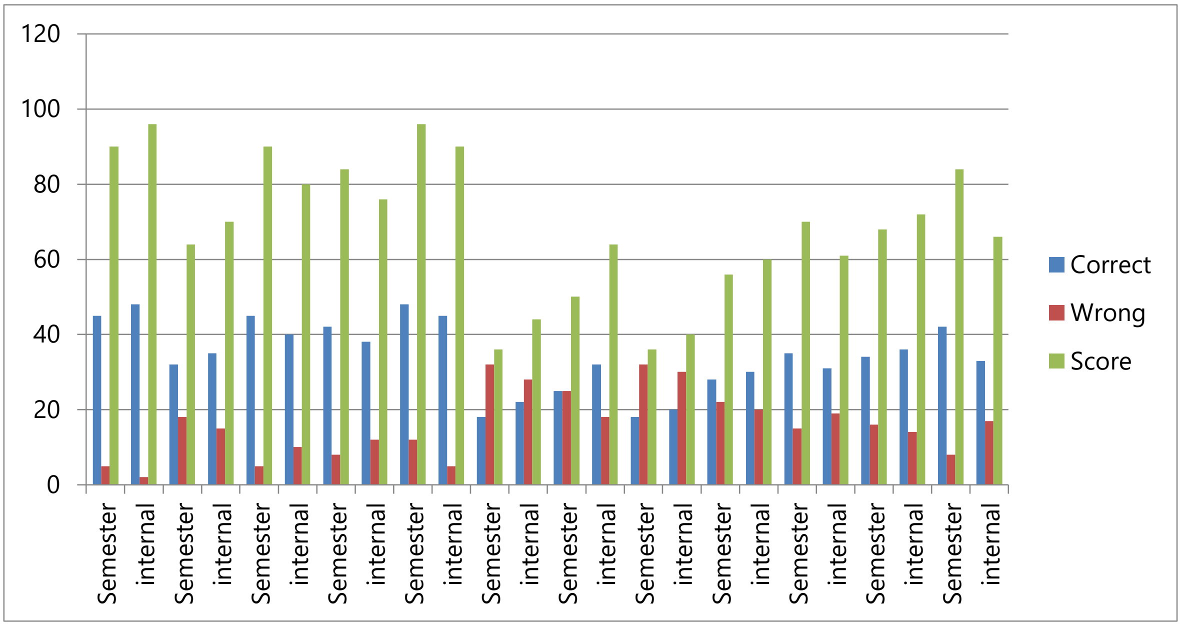

Figure 3Comparison of IT and ST

7. CONCLUSION

Predicting student success beforehand is crucial, and we have found through comprehensive research that different student datasets provide varying outcomes of varying quality. The aim of our research is to anticipate the potential of an undergraduate exhibition and develop an exceptional framework for advanced learning[26]. We seek to analyze the consistency of assumptions regarding the likelihood of a student's role and evaluate the effectiveness of knowledge mining methods in this context. By using a Knowledge-Based Decision Support System (KDSS) to analyze actual student performance, we can make better decisions and improve the efficiency of the examination process to reduce students' exam phobia. Expert systems can help solve student-related problems and bridge any gaps between different types of examinations, reducing the pressure of exams and preparing students for new challenges. In future work, we plan to use machine learning techniques to set tougher internal exams for practice and reduce the toughness of ET exams according to the data sets.

Reference

[1] Kabakchieva, D., Predicting student performance by using data mining methods for classification. Cybernetics and information technologies, 2013. 13(1): p. 61-72.

[2] Osmanbegović, E. and M. Suljić, Data mining approach for predicting student performance. Economic Review, 2012.10(1). [3] Käser, T., N.R. Hallinen, and D.L. Schwartz. Modeling exploration strategies to predict student performance within a learning environment and beyond. in Proceedings of the Seventh International Learning Analytics & Knowledge Conference. 2017. ACM.

[4] Marquez-Vera, C., C.R. Morales, and S.V. Soto, Predicting school failure and dropout by using data mining techniques. Tecnologias del Aprendizaje, IEEE Revista Iberoamericana de, 2013. 8(1): p. 7-14.

[5] Rovira, S., E. Puertas, and L. Igual, Data-driven system to predict academic grades and dropout. PloS one, 2017. 12(2): p. e0171207.

[6] Ahmed, A.B.E.D. and I.S. Elaraby, Data Mining: A prediction for Student's Performance Using Classification Method. World Journal of Computer Application and Technology, 2014. 2(2): p. 43-47.

[7] Tamhane, A., et al. Predicting student risks through longitudinal analysis. in Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining. 2014. ACM.

[8] Daud, A., et al. Predicting Student Performance using Advanced Learning Analytics. in Proceedings of the 26th International Conference on World Wide Web Companion. 2017. International World Wide Web Conferences Steering Committee.

[9] Adhatrao, K., et al., Predicting Students' Performance using ID3 and C4. 5 Classification Algorithms. arXiv preprint arXiv:1310.2071, 2013.

[10] Aher, S.B. and L. Lobo. Applicability of data mining algorithms for recommendation system in elearning. in Proceedings of the International Conference on Advances in Computing, Communications and Informatics. 2012. ACM.

[11] Ikbal, S., et al., On early prediction of risks in academic performance for students. IBM Journal of Research and Development, 2015. 59(6): p. 5: 1- 5: 14.

[12] Ktona, A., D. Xhaja, and I. Ninka. Extracting Relationships between Students' Academic Performance and Their Area of Interest Using Data Mining Techniques. in Computational Intelligence, Communication Systems and Networks (CICSyN), 2014 Sixth International Conference on. 2014. IEEE.

[13] Márquez-Vera, C., et al., Predicting student failure at school using genetic programming and different data mining approaches with high dimensional and imbalanced data. Applied intelligence, 2013. 38(3): p. 315-330.

[14] Mgala, M. and A. Mbogho. Data-driven intervention-level prediction modeling for academic performance. in ICTD. 2015.

[15] Shahiri, A.M. and W. Husain, A Review on Predicting Student's Performance Using Data Mining Techniques. Procedia Computer Science, 2015. 72: p. 414-422.

[16] Bunkar, K., et al. Data mining: Prediction for performance improvement of graduate students using classification. in Wireless and Optical Communications Networks (WOCN), 2012 Ninth International Conference on. 2012. IEEE.

[17] Jishan, S.T., et al., Improving accuracy of students' final grade prediction model using optimal equal width binning and synthetic minority oversampling technique. Decision Analytics, 2015. 2(1): p. 1.

[18] Mayilvaganan, M. and D. Kalpanadevi. Comparison of classification techniques for predicting the performance of students academic environment. in Communication and Network Technologies (ICCNT), 2014 International Conference on. 2014. IEEE.

[19] Ramesh, V., P. Parkavi, and K. Ramar, Predicting student performance: a statistical and data mining approach. International journal of computer applications, 2013. 63(8).

[20] Elakia, G. and N.J. Aarthi, Application of data mining in educational database for predicting behavioural patterns of the students. Elakia et al,/(IJCSIT) International Journal of Computer Science and Information Technologies, 2014. 5(3): p. 4649-4652.

[21] Mishra, T., D. Kumar, and S. Gupta. Mining Students' Data for Prediction Performance. in Advanced Computing & Communication Technologies (ACCT), 2014 Fourth International Conference on. 2014.IEEE.

[22] Arsad, P.M., N. Buniyamin, and J.-l.A. Manan. A neural network students' performance prediction model (NNSPPM). in Smart Instrumentation, Measurement and Applications (ICSIMA), 2013 IEEE International Conference on. 2013. IEEE.

[23] Gray, G., C. McGuinness, and P. Owende. An application of classification models to predict learner progression in tertiary education. in Advance Computing Conference (IACC), 2014 IEEE International. 2014. IEEE.

[24] Jagjit Singh et al. “Multi-agent based decision Support System using Data Mining and Case Based Reasoning” IJCSI International Journal of Computer Science Issues, Vol. 8, Issue 4, No 2, July 2011, ISSN (Online): 1694-0814

[25] Jagjit Singh D et al“The Role of MAS Based CBRS using DM Techniques for the Supplier Selection” 2347-2693, 2019 Vol-7 & Issue no. 5 1658- 1665

[26] Jagjit Singh D et al.“Implementation of Case Base Reasoning System using Multi-Agent System Technology for a Buyer and Seller Negotiation System” International Journal of Electronics and Communication Engineering 2321-2152, 2019 Vol-7 & Issue no. 3 63-67

[27] Kuldeep Singh Kaswan, “A New Nature Inspired Optimization Technique”, published in the "International Journal of Advanced Research Engineering and Technology (IJARET)", Volume 12, Issue 2, 2021. .

[28] Kuldeep Singh Kaswan, “Big Data Reliability: A Critical Review”, published in Journal of Intelligent & Fuzzy Systems, Volume 41, pp. 1-16, 2021. DOI: 10.3233/JIFS-202503.

[29] Kuldeep Singh Kaswan , “A Hidden Markov Model based Prediction Mechanism for Cluster Head Selection in WSN”, International Journal of Advanced Science and Technology Vol. 28, No. 15, (2019), pp. 585-600.

[30] Kuldeep Singh Kaswan , “Face Acknowledgement Framework Using Hybrid of Genetic Algorithm and Ant Colony Optimization Algorithm”, International Journal of Scientific & Technology Research Volume 8, Issue 11, November 2019 ISSN: 2277-8616. .

[31] Kuldeep Singh Kaswan, “Fault Model for UML Behavioral Activity and Sequence Diagrams”, International Journal of Engineering and Advanced Technology (IJEAT), ISSN: 2249 – 8958, Volume-9 Issue-1, October 2019.