Implementation of Precision Education System Based on Machine Learning Model

G. Shanmugasundar[1], Jasgurpreet Singh Chohan[2], and Kanak Kalita[3,4](✉)

[1] Department of Mechanical Engineering, Sri Sai Ram Institute of Technology, Chennai 600044, India
shanmugasundar.mech@sairamit.edu.in

[2] Department of Mechanical Engineering and University Center for Research & Development, Chandigarh University, Mohali 140413, India
jasgurpreet.me@cumail.in

[3] Department of Mechanical Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi 600062, India
kanakkalita02@gmail.com, drkanakkalita@veltech.edu.in

[4] Jadara University Research Center, Jadara University, Irbid 21110, Jordan

Abstract. Precision Education (PE) is an approach that emphasizes the use of various forms of technology to personalize students' educational opportunities according to their unique requirements. In order to facilitate effective learning that is suited to the needs of each individual, it is necessary to have complete information about the learning process. PE describes a personalized approach to classroom instruction. We propose Dignified Reinforcement Learning (DRL) which includes all the essential elements required for PE, in order to determine the impact of developing multimodal innovations on individualized learning. The system aims to address issues with the standard model of education analysis, such as insufficient internal validity, predictive validity, timeliness, comparability, and understandability, in order to provide more precise instruction. Networking sites, the digital classroom, the intelligent agent, and the panel are the four fundamental aspects of an RL-based technology. Through model-based RL, the head attribute of the continuous educational environment gathers and processes a multimodal flow of student records from the various modules to create laws of appropriate behaviors that optimize the long-term benefits for both the individual and the computer. To demonstrate the usefulness of the proposed model, experimental evidence was presented using a subset of multimodal data. Practical and theoretical implications for future digital learning approaches and investigations may be drawn from RL systems.

Keywords: Precision education (PE) · dignified reinforcement learning (DRL) · multimodal innovations · individualized learning · fundamental aspects · digital learning approaches

P. Vasant et al. (Eds.): ICO 2023, LNNS 1167, pp. 135–145, 2024.
https://doi.org/10.1007/978-3-031-73318-5_14

1 Introduction

The use of artificial intelligence (AI), machine learning (ML), and online courses may lead to improvements in student outcomes and teacher efficacy. The academic data of learners' offline and online training activities, achievements, and communication are considered to play a crucial role in virtual learning networks' ability to promote precision education. Two domains, academic data gathering and behavioral analysis, are seen as key to integrating and exploring big data capabilities in the curriculum, made possible by the increasing amounts of data being gathered from different e-learning systems [1]. As a result, researchers have heavily focused on studying learners' interactive learning behavior and segmenting individuals exhibiting particular learning characteristics across different online educational technologies. By evaluating students' online training habits and implementing them in a timely manner, precision education was shown to predict students' educational objectives from the curriculum. The engineering education model is a convenient shorthand for describing the goals of physical education [2]. Another academic definition of precision education emphasizes that its primary goal is to diagnose, anticipate, manage, and protect student problems as soon as possible. These four pillars suggest that the primary areas of study in precision education are the following: the evaluation of teaching methods; the prediction of participants' academic achievement; the intervention with teaching techniques and exercises; and the preventative design [3]. The model of science and technology, in which network analysis and control principles are fundamental foundations, offers some further understanding. Numerical simulations are used in a systems approach to describe systems, allowing for the estimation of the program's condition and evaluation of the individual based on that condition. Figure 1 shows the comparison of learning activities [4].

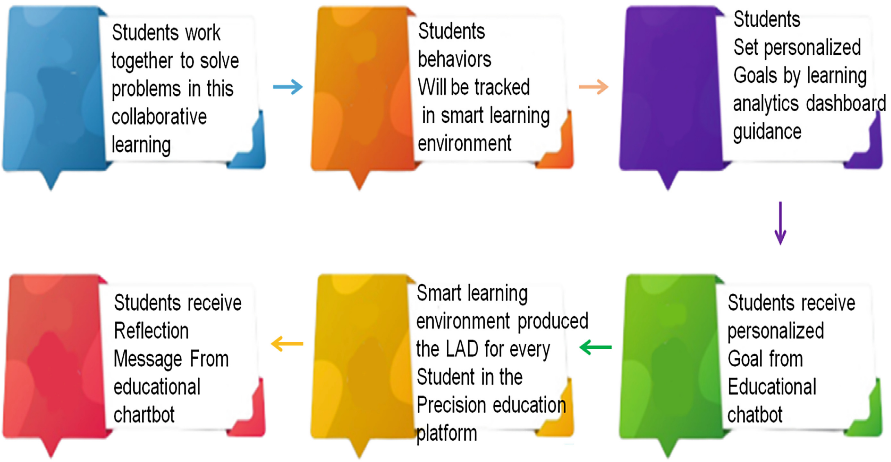

Fig. 1. Learning activities in educational sector

The physical education strategy can be divided into two main components: targeted instruction and targeted study. The strategic use of student information to create a customized program that suits their educational needs is an emerging area of research for academic improvement. One can draw parallels between the global positioning framework used by online users and the processes required to achieve the latter idea [5]. The primary goal is to ensure that the training objectives set for the students are understood. These include the ability to articulate their requirements more effectively and a clearer understanding of their current skill set. Additionally, information on how to capitalize on opportunities for moderate achievement should be made available [6].

Aiming high is essential for achieving high-quality education. This requires a meeting of minds among specialists in fields such as genetics, neurology, behavior, and psychology to discuss how learning occurs and whether different individuals' educational needs can be met by combining different resources. As demonstrated by the fields of genetics, neuroscience, and information theory, which investigate not only external sensory stimuli but also the internal workings of the mind, providing precision education involves the collection of vast amounts of personal information [7]. The major limitations in achieving this goal are being addressed, and we propose the use of dignified reinforcement learning (DRL).

2 Related Works

Coulibaly et al. [8] presented VGG16 as a means to create an authentication protocol for mildew illness in cereal grains by combining transfer learning with feature extraction. In precision farming, deep learning (DL) enables a rapid and engaging analysis process. One benefit is that the logic offers significant constituents of data and understanding. Cook et al. [9] discussed the importance of precision education (PE), presented criteria and explanations, and outlined the potential to expand the understanding of PE to set the scene for the special issue. In order to improve the design of strategies towards gaining students' learning, they need a more realistic view of action, which entails logistical initiatives to increase the accuracy of services for participants with educational, behavioral, sentimental, or health issues.

Qushem et al. [10] examined how these characteristics are used in practice and discussed programs that utilize them. They demonstrated that using PE methods with digital learning technologies and platforms might enhance students' information retention and advancement opportunities. Additionally, they highlighted how PE may improve students' confidence, academic performance, and overall health. In line with the ideas and proposals made by proponents of PE, they provide a basis for developing policies and strategies on how multimodal technology can be integrated into the academic environment.

Williamson [11] proposed the field of digital policy sociology as a new approach to investigating the impact of digital technology on educational guidelines. By combining established "policy sociology" methods with developing "virtual sociology" findings, "digital strategy social work" broadens the focus of analysis to include autonomous hardware and software along with people specialists, tech businesses, and advocacy groups. During the epidemic, e-learning, the use of new digital educational material, limitations of web access, and miscommunication between instructors and students exacerbated the difficulty of special activity. Adapting methods from research that only considered one pathway to produce a forecast decreases the superior predictive potential because it simply includes a portion of the properties of each conceivable path. Clustering occurs frequently due to insufficient data for each session, making it difficult to ascertain the participant's level of engagement throughout the academic track or in a greater perspective. They explained how to solve these problems by developing an adaptable and universal framework [12]. Due to the challenges in the existing work, we propose using DRL for implementing PE.

3 Proposed Methodology

Educational innovation is a critical component of today's classrooms as it allows for more personalized instruction and improves students' retention of material. Innovation has been used as an educational tool for a long period. Therefore, online learning in primary school is a relatively new development when compared to other stages of education. Figure 2 demonstrates the working mechanism of the suggested method after the information has been gathered and preprocessed.

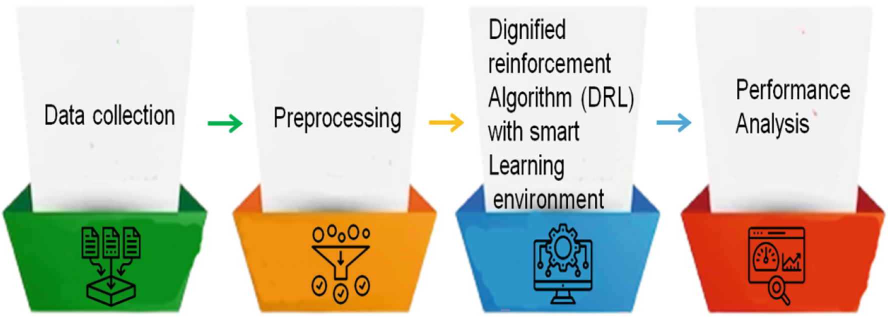

Fig. 2. The working flow of the suggested method

3.1 Data Collection of Samples

Fifty participants' files from one master's program in management were obtained for this investigation. Information such as ID number, age, bachelor's degree name, bachelor's cumulative GPA, master's graduate programs performed, scores earned, and program supervisors are kept in such databases. Table 1 shows the most frequently used characteristics, attributes, as well as other relevant information. Table 2 displays qualitative data for the two datasets derived from these data. As part of the institution's commitment to privacy protection, these documents were made available after identities and card numbers had been changed for students and faculty.

Table 1. Characteristics, attributes and relevant information of the dataset

Features of Students	Type of data	Information about features
Student number	Ordinal	1,2,3 4, …., 52 (total were 50 students)
Age	Ratio	In between 30 and 52
Program title	Nominal	AI and organizational learning overview, …
Names of Faculty Members	Nominal	Faculty 1, Faculty 2, …
Bachelor degree	Nominal	System of information, computer science, …
Bachelor grade	Ordinal	3.25, 3.62, …
Program results	Ordinal	A, B, C, & F

Table 2. Qualitative data analysis from dataset

Descriptional Metrics	Dataset 1	Dataset 2
Indispensable Factors (IF)	Grades (All Courses Grades)	Grade (Dissertation Grade)
Statistics of occurrences	273	38
IF Middle value	4	4
IF Average	3.39	3.44
Starting point of precision	P (4) = (136/234) % = 58.1%	P (4) = (23/38) % = 60.5%
IF Condition	4	4

3.2 Technology

Several adjustments were made to the provided data to prepare it for analysis. To do this, we employed Excel Software in addition to the Python Integrated Developer Environment (version 3.6.2). R Studio (version 1.1.456) was also used to present the information and select the most important characteristics. Additionally, it was used to train the information using various classifiers and then analyze that approach to determine which one is the most effective for ML identification.

3.3 Preprocessing Using Normalization

Data points need to be cleaned and prepared before being fed into the evaluation stage since they often include useless variables, lacking circumstances, and unsuitable data formats for features. This resulted in the following procedures being applied to the feature sets: before training a sample using a classifier or optimization method as a computational ML algorithm, normalization is a commonly suggested pre-processing method. Scaling the samples' values to fall inside [0, 1] or [–1, 1] often yields good outcomes. R used the following expression (assuming the range is [a, b]) to determine the normalizing technique for this research, and MinMaxScaler (which scales instances to the range [0, 1]) was utilized for the scaling.

$$Y - Normalized < -([b - a] * (X - \min(X))/(\max(X) - \min(X)) + a \quad (1)$$

3.4 Dignified Reinforcement Learning Algorithm (DRL)

The limitations mentioned earlier can be overcome through the more general ML approach of Dignified Reinforcement Learning (DRL). DRL can execute micro-simulations continuously, collect data from various sensory sources, and select an appropriate course of action. Compared to other ML algorithms, DRL focuses more on goal-oriented training through interaction with the environment. The robot knows what it wants, observes its surroundings, and selects an appropriate response or modification. Unlike supervised and unsupervised learning, DRL develops behavior through repetitive interactions with the environment and the response it receives. Therefore, DRL is similar to how humans and animals acquire skills through training. Like how people make judgments based on the current situation and choose the relevant action, the RL-based operator uses the principle of reinforced behaviorism. When its strategy starts to yield benefits, it may decide to keep it in place and make minor adjustments to achieve the greatest possible long-term payoff.

3.5 The Mechanism of Precision Education (PE)

To address the limitations of current formative assessment, a human-machine hybrid RL architecture must be developed for precise learning. Specifically, humans can provide principles that support the development of domain expertise and just-in-time knowledge, reducing computing complexity and enhancing learning outcomes. People can collaborate with the RL machine to optimize incentives, even during rigorous training sessions, by providing competitive education for accurate value judgments. The outcome of learning is complex and rendered useless if it cannot be analyzed by individual specialists in regards to the specific kind of knowledge creation. Therefore, dynamic visualization and analysis tools can be used to display digital learning findings, offering students and educators a relevant interpretation. Additionally, humans can provide specialized skills in RL's sensitivity to insufficient knowledge since they are experts in this field.

3.6 Characteristics of the Central System

Connectionism and RL both agree that the brain is the most critical component of any system. When combined, in continuous teaching situations, the brain analyzes heterogeneous input sources from students to construct a symbiotic training algorithm. The online communities' factor can digitize the source code of supervised and design data and attributes. The clever guidance aspect can collect information about student participation, visual expression, physical performance, sensory information, and immediate evaluation reactions. The automated learning aspect can gather information on consultations and discussions, while the center console element can collect information about human-computer communications and data visual analytics. The network establishes a policy to select measures related to student learning using techniques that maximize the weighting scheme for the highest benefit. The incentive instead informs the central part about the activity's consequence in a continuously changing manner, allowing the central part to self-organize. To accommodate the effectiveness, implementation, and functional requirements of emerging real-time ML, the central component features response time and maximum speed, task scheduling formation, flexible high availability, debug ability and screening, and random dynamic data interrelations.

3.7 Attributes of Social Interaction

The next section focuses on students' online social networking profiles, which include their online artifacts demonstrating their intellectual, emotional, and social growth. An important factor in students' results is the setting in which they are utilizing social networks, including how much they are using it. Participants who had communications and postings supported by two or more machines performed better overall in the program, whereas students who had less information approved by three machines performed worse. Individuals' success in global learning analytics may be predicted mostly by the substance of the interactions they engage in. In addition, students' happiness and their impressions of their own learning are correlated with their ability to observe and interact with individuals in their virtual classroom. Therefore, in global learning analytics, the postings and responses students make among classmates and teachers, as well as their responses to the signals of others, are crucial emotional and cognitive artifacts.

3.8 Technology-Integrated Education

Finally, the use of modern technology in education is also discussed. It involves utilizing various sources of information for online learning and focuses on classroom-based analysis, surveillance, peer-instructor interaction, and educational adaptation. According to connectivism, the basis of education is the free and open sharing of ideas. In-class discussions and mutual questioning and answering between students and teachers can be beneficial for both parties. However, in university settings, large class sizes can hinder teacher-student interactions, leading to negative outcomes such as increased attrition and persistence rates. The use of student evaluation platforms has been found to increase opportunities for productive conversations between students and instructors, as well as among learners themselves, in the classroom. Additionally, if teachers use predictive exams with suitable approaches based on statistical feedback from the central component, they can quickly identify misunderstandings and provide immediate scaffolding or clear explanations to address the issue. Moreover, wearable devices for learners can encourage active participation and idea sharing, which can be a valuable tool in combating apathy and conformity in the classroom.

3.9 Agent-Based Intelligence

In the fourth position, we have the smart agent. Due to time and location restrictions, the student may not be able to create as much or as widely applicable information with their teacher and classmates as they may want. The intelligent agent aspect may mediate between the material, the student, and the teacher to facilitate information exchange and production, so mitigating a potential drawback in the form of a lack of few assessments and scaffolding. Autonomous robots are A.I. systems that use ML and NLP to provide interactive, multilingual, and contextualized education. Within proximal development zone intelligent agents may assume the function of the more informed someone else by providing assistance in accomplishing the job at hand, addressing fundamental queries, or inspiring students to engage in reflective or metacognitive thinking via natural discourse. In addition, intelligent agents can adapt to students' traits and requirements, making personalized learning more effective. However, most autonomous robots were always dependent on predefined rules and may not be able to handle complex, unpredictable situations.

3.9.1 Aspects of a Panel

The final part is a panel that collects, cleans, stores, manages, and displays information about each patient's sensor data and their academic ability. Learning interpretive monitoring systems offer several benefits, including facilitating participants' self-regulated learning through characteristics like self-monitoring and self-assessment, supplemented with individualized responses. It also helps identify participants' roles in digital training and their interactions with others. Participants can use accessible metrics to evaluate how they perform compared to both their peers and the top performers in the classroom. However, designing a teaching developer console still faces several obstacles, such as 1) modeling the complexities of education, 2) considering students' knowledge, 3) restricting the modality of student records, and 4) integrating academic data gathered from a single console.

4 Performance Analysis

Precision education (PE) is an approach for detecting learners who are at risk of dropping out. Identifying vulnerable students at an early stage allows for more targeted interventions to be made. The importance of accuracy in the classroom has grown as the field of education has progressed. PE is successful in physical education because it takes a detailed look at each student's progress and requirements, which helps keep them engaged and in school and helps educators find the right balance. Evaluating the success of an intervention requires monitoring the learner for a while after it has been applied. Additionally, contemporary trainers see PE as a challenging opportunity to improve their personal instructional practices and their learners' academic outcomes. The findings of the PE analysis are presented here for the benefit of learners. To achieve this goal, we have examined indicators such as prediction accuracy [13], average course outcomes, and the effectiveness of the training phase [14].

4.1 Prediction Accuracy

The most surprising findings from the digital tools were the low computational complexity and instantaneous nature of precision educational models. Learners mostly use their personal mobile devices for app development and testing, but these devices are often older and less powerful than ideal for the task. Predictions made by the programs were mostly unreliable. In fact, typically only the team that built the app was satisfied with the prediction reliability. Improving predictions with noise data had poor outcomes. Developing accurate forecasts in the presence of ambient noise was seen as particularly challenging. It is possible that better prediction accuracy could be achieved with more time and a more diverse testing dataset. Figure 3a illustrates the prediction accuracy of PE. The number of learners who may have implemented PE to make predictions is analyzed, and the results are as follows:

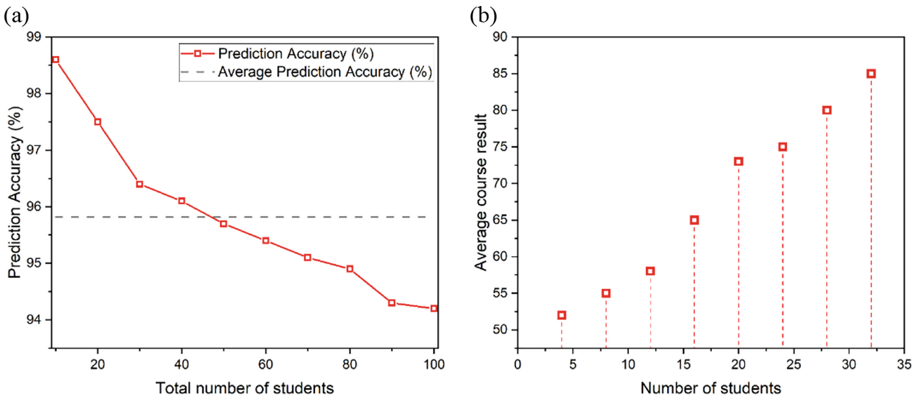

Fig. 3. (a) Prediction accuracy of PE (b) Average course results from students

4.2 Average Course Results

Among students who completed the training reflection, self-assessment, and goal-setting procedure, there was a 4.32-time log-in rate on average. The writers separated the students into two categories based on how often they completed the procedure. Data showed that 21 participants (42% of the class) had a higher completion percentage than the median. The overall average performance was 86.966 out of 100. The average grade for the 29 students who scored below the class average was 79.572. Students who had completion rates higher than the class average also had a greater tendency and lower standard variance for their course grades. Figure 3b shows statistics for the entire class.

4.3 Training Process and Control Techniques

Figure 4 shows that there are variations in the profiles of the training process and control techniques at a significantly more granular level. There are statistically significant differences among the groups for associating and organizing, for ExtRegRes (external regulation of learning outcomes), and for absence of regulation. Regarding cognitive load, more advanced profiles have more advanced machine learning and less advanced concrete learning. The amount of external control of learning outcomes is positively correlated with the learner's profile and negatively correlated with the learner's absence of credentials. Q refers to the four quadrants.

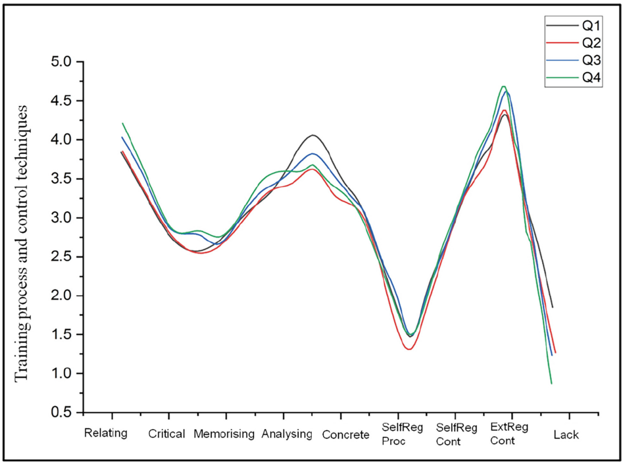

Fig. 4. Training process and control techniques

5 Conclusion

The goal of precision education (PE) is to enhance student performance and educator effectiveness through the use of various learning algorithms. It has been observed that virtual learning systems play an essential role in collecting the credentials of students' physical and digital learning activities, facilitating precision education. However, a single investigation is insufficient to assess accuracy. Accurate evaluation requires a wide range of considerations and explorations. To overcome these limitations, we suggest using the deep reinforcement learning (DRL) method to build PE. The suggested study successfully evaluated learners' interest in both traditional and rigorous pedagogy with an accuracy of %. In future work, the advanced protocol may be employed for this goal.

References

1. Alsharhan A, Salloum SA, Aburayya A (2021) Using e-learning factors to predict student performance in the practice of precision education. J Legal Ethical Regul Issues 24:1–14
2. Matthews LJ (2020) Precision (Mis) education. Hastings Center Report, vol 50
3. Mertanen K, Vainio S, Brunila K (2022) Educating for the future? Mapping the emerging lines of precision education governance. Policy Futur Educ 20:731–744
4. Liu T-C (2022) A case study of the adaptive learning platform in a Taiwanese elementary school: precision education from teachers' perspectives. Educ Inf Technol 27:6295–6316
5. Luan H, Tsai C-C (2021) A review of using machine learning approaches for precision education. Educ Technol Soc 24:250–266

6. Hu Y-H (2022) Effects and acceptance of precision education in an AI-supported smart learning environment. Educ Inf Technol 27:2013–2037
7. Yang SJ, Ogata H, Matsui T, Chen N-S (2021) Human-centered artificial intelligence in education: Seeing the invisible through the visible. Comput Educ Artif Intell 2:100008
8. Coulibaly S, Kamsu-Foguem B, Kamissoko D, Traore D (2019) Deep neural networks with transfer learning in millet crop images. Comput Ind 108:115–120
9. Cook CR, Kilgus SP, Burns MK (2018) Advancing the science and practice of precision education to enhance student outcomes. J Sch Psychol 66:4–10
10. Qushem BU, Christopoulos A, Oyelere SS, Ogata H, Laakso MJ (2021) Multimodal technologies in precision education: providing new opportunities or adding more challenges? Educ Sci 11:338
11. Williamson B (2021) Digital policy sociology: Software and science in data-intensive precision education. Crit Stud Educ 62:354–370
12. Asad R, Altaf SM, Ahmad S, Shah Noor Mohamed A, Huda SA, Iqbal S (2023) Achieving personalized precision education using the Catboost model during the COVID-19 lockdown period in Pakistan. Sustainability 15:2714
13. Prasad PY, Prasad D, Malleswari DN, Shetty MN, Gupta N (2022) Implementation of machine learning based google teachable machine in early childhood education. Int J Early Child 14:2022
14. Tempelaar D, Rienties B, Nguyen Q (2021) The contribution of dispositional learning analytics to precision education. Educ Technol Soc 24:109–122