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Design of an Improved Method for Personalized Learning Using Deep Q-Learning and CNN-Based Engagement Recognition

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Abstract:

Adoption of personalized learning systems is on the rise. Traditional approaches to education, in most cases, cannot fulfill the diversified requirements of different learners and target various levels of engagement. Current methods are mainly focused on defined learning paths or limited information regarding levels of engagement, hence failing the adaptability test, which prevents real-time understanding and leveraging of data in such cases. This paper fills in the identified gaps by proposing a holistic, multi-faceted learning system and incorporating three advanced machine learning techniques: Deep Q-Learning for personalized content recommendations, Random Forest Classifier for predictive academic analytics, and Convolutional Neural Networks (CNNs) for real-time engagement tracking. Deep Q-Learning is used for adaptive providing learning resources by using the performance metrics of students in quizzes and the timestamp spent on tasks to optimize learning paths based on real-time feedback. Random Forest Classifiers will be used as they are robust for predicting academic success by using historical academic data as well as the engagement metrics gathered from smart classrooms. This includes the application of CNNs in visual engagement recognition, such as detecting a child's attention levels based on facial expressions and body language. Real-time engagement data is fed back into the learning system to further refine the contents recommended and academic predictions made. A dynamic and highly personal environment in the learning process is created through these practices by virtue of the continuous optimization of content and predictions based on individual student interactions. Preliminary results so far indicate a likely 20-30% improvement in learning outcomes, with around 85-90% accuracy in academic predictions, and a 15-20% increase in classroom engagement. This is highly sophisticated intelligent learning and offers best tools for faculty to improve performance and engagement.

Keywords: Personalized Learning, Deep Q-Learning, Random Forest Classifier, CNN Engagement Recognition, Smart Classrooms

1. Introduction

Using technology in schools is drastically changing the educational landscape. Recent years have seen drastic changes, especially AI and ML, in schools. Generally, the purpose of all these technological interventions is to customize the content, delivery, and pace of learning for individual students to make learning a better experience in the process. Most personalized learning systems currently existing suffer from their reliance on static models or simple rule-based algorithms that truly cannot adapt well to the subtleties of real-time student data samples. As such, approaches are urgently in demand [1, 2, 3] that are more complex and sophisticated enough to tackle the intricate dynamicity of modern-day classroom settings. Deep Q-Learning will allow an agent, here the learning system, to learn optimally occurring strategies by interacting with an environment, in this case, the classroom, and receiving rewards based on his actions, for example, recommending that particular type of learning material. It will continue to be the optimization of pathways since the system may keep changing its recommendations as student performance and engagement data start evolving. Indeed, Deep Q-Learning is particularly applicable in smart classrooms, characterized by large and complex state spaces where every input of the learning environment, such as student behavior, engagement, and performance metrics, impacts the outcome.

Another critical design element of smart learning systems involves the prediction of academic outcomes by historical datasets and real-time data samples. In the educational field, predictive analytics is used extensively to predict the likelihood of a student's success or failure levels. Still, many models [4, 5, 6] are designed based on only academic variables like grades and attendance without considering the critical behavioral and engagement factors involved in the depiction of learning outcomes. To fill this gap, this paper proposes that Random Forest classifiers, which are strong and capable of handling high-dimensional data, may be appropriate for the task of making predictions about academic achievement based on metrics both from academics and engagement. Predictive analytics as well as personalized content recommendations can enhance learning outcomes immensely, but the bottom line for any educational intervention is student engagement. Engagement is the level of attention, interest, and participation demonstrated by students, and it is a critical determinant of learning success. Traditional approaches to measuring student engagement through subjective self-reports or observations by teachers are of highly subjective nature and biased. Recent improvements in computer vision combined with deep learning, particularly Convolutional Neural Networks (CNNs), have made objectivity and scalability more feasible techniques for analyzing engagement. In using CNN for image recognition tasks, video feeds from smart classrooms can be processed to assess engagement levels in real time. These visual signs-including facial expressions, eye gaze direction, or even body posture-can be used in analyzing the input by CNNs in order to give very accurate instantaneous appraisal of a student's level of engagement. This information can be fused into a personalized learning system, allowing teachers to intervene promptly whenever the level of engagement starts to drop.

This represents a new approach to personalized education wherein advanced machine learning techniques such as Deep Q-Learning, Random Forest classifiers, and CNN-based engagement recognition are integrated into a single system. Real-time data from smart classrooms can then be used to dynamically adjust learning paths and make accurate predictions about the acquisition of outcomes - all of this happening while the engagement levels of students are monitored and responded to. This paper elaborates on the design and evaluation of such a system with emphasis on the interplay among different models of machine learning and the impact of their integration upon students' performances and engagement. Preliminary experimental trial results show that this proposed system can significantly improve the learning experience. In the personalized recommendation, Deep Q-Learning outperformed traditional static learning models by 20-30%. The use of Random Forest classifiers coupled with achieving between 85% and 90% of accuracy where it is possible to predict achievement or failure. It then added 10-15% more to this prediction accuracy by incorporating engagement metrics. Apart from this, CNN-based real-time tracking of engagements has enabled teachers to intervene just in time. In effect, class participation increased by 15-20% overall. Overall, this paper describes an integrated and comprehensive solution for P Learning that consists of the best aspects of RL, PA, and DL-based engagement analysis. This research will help improve educational outcomes in smart classrooms by tackling the limitations of existing systems and introducing a new multilevel approach.

Motivation & Contribution

The rationale of the present study is based on the fact that more and more acknowledgment about the critical limitations that exist in conventional stationary education models dealing with all students as if they belong to a homogenized unit is now coming up. Actually, students show immense diversities in their learning style, interest, as well as cognitive skills, but most of the contemporary systems are not addressing them. Personalized learning is an idea that has been established and discussed quite prominently in educational research and can be a solution to such a problem. However, the majority of current personalized learning systems rely on predefined rules or static algorithms that do not change dynamically according to changes in behavior or performance of students. Also, most currently used predictive models focus primarily on academic factors, such as grades or attendance, while neglecting behavioral and engagement metrics that significantly weigh into the building trajectory of learning of a student. This research is motivated by the need for a more vibrant and integrated system that not only responds to the diverse learning needs of each learner but can also embrace real-time engagement data and predictive analytics toward improved education outcomes.

The first and principal contribution of this work is in the development of an integrated machine learning-based system that combines Deep Q-Learning for personalized content recommendations, Random Forest classifiers for academic outcome prediction, and CNN-based recognition of engagement, which supports understanding the behavioral patterns of students in real-time. This approach has a unique strength in each; Deep Q-Learning for the optimizing of decision-making in complex environments, Random Forests for robust dealing with big high-dimensional datasets, and CNNs for high accuracy in visual pattern recognition to help in engagement detection. The proposed system brings all these methods together to give the world its own personalized learning system that is adapted automatically to real-time student data samples. This system provides personalized content as well as predicting a person's academic performance with a high accuracy, thus allowing for intervention and adjustment in good time. The research also demonstrates how such engagement data can seamlessly be integrated into the learning process, meaning that a teacher can immediately adjust teaching based on actual feedback. The upshot is a holistic adaptable tool of highly effective education that precipitates marked improvements in both student engagement and performance.

2. Review of Existing Models for Student Engagement Analysis

Personalized learning recently provoked great enthusiasm around the world with rapid advancement in machine learning, artificial intelligence, and data analytics. In recent innovations and rapid improvements in how traditional educational models are fitted to match students' differing needs and levels of interest, personalized approaches to learning promise to tailor content to an individual student to ensure better engagement, motivation, and outcomes. Table 1 Review The implementation of different methodologies to address the challenges that are involved in personalizing education is reflected by the review in table 1. A strong effectiveness of machine learning and personalized interventions in improving student engagement, academic performance, and motivation can be understood when all these papers are put together; however, this incredibly wide array of educational environments and learning domains is concerned. One of the themes that appear frequently in these papers and is very prominent is to use data-driven approaches in identifying, then addressing individual learning needs. For example, Yang and Ogata [1] and [2] report two different applications of personalized learning analytics, namely improving engagement in blended learning as well as third language learning through e-books, respectively. Each study showed the validity that the data-informed intervention will have a tremendous positive effect on students' academic performance and behavioral engagement, thereby offering new prospects for using personalized learning analytics to support the better use of teaching strategies. However, in some critical areas, these studies point out the limitations of such intervention research: it studies outcomes in specific subjects, and has generally been implemented over only a relatively short period of time so that it does not determine retention or deeper learning. Similarly, Wang [3] presented an idea for a deep learning-based personalized recommendation system for music education, that is, focused on Guzheng Pedagogy. The application, though niche, indicates a 10% efficiency in learning; thus, deep learning techniques do apparently possess the functionality towards improving the outcomes of learning by associating the content with the needs and preferences of individual learners. The applicability of the method, however, is restricted due to specificity. Other authors, for example, Drissi et al. [4], explored gamified frameworks of mobile learning combined with personalized recommendations as well, which demonstrate that gamification combined with personalized interventions can promote student motivation as well as their learning achievement even more. Combining personalization and engaging elements, like games, makes the learning process more interactive, thus motivating students to be participants in the process. Such gamified approaches are however limited in their effectiveness within non-gamified, more traditional learning environments where motivational dynamics are different.

Another crucial aspect that is investigated in the considered papers is the involvement of self-regulation and engagement in personalized learning. Studies by Liu et al. [5], and van der Graaf et al. [9] consider how self-regulated learning strategies impact cognitive engagement and achievement in learning. The research studies go on to highlight the need for including such personalized scaffolds and feedback loops in ed-tech tools to develop the ability to learn autonomously. Notably, results from these studies show that there is an improvement in tasks being completed and in learning outcomes when students receive real-time feedback and scaffolding mechanisms designed based on each individual's learning progress. What is lacking in this study is the inability to implement its design in conjunction with real-time engagement metrics or behavioral data, which are essential elements for learning paths to be adjusted dynamically. This opens up possible avenues for more comprehensive, real-time feedback mechanisms in future research through the complementarity of both cognitive and behavioral metrics. On a different tack, Dumont and Ready [6] spoke to the ability of personalization to further educational equity in their research on this alternative tool. Though their bottom line was less optimistic than that of the aforementioned two studies, it suggested that personalized learning systems were able to support failing students by means of resources and support customized to fit their learning needs. This is an important feature of personalized learning, although one which could--especially with the high-achieving students--potentially mitigate achievement gaps for students coming from different academic backgrounds. The constraint on scalability is that personalization typically requires complex data processing and teacher involvement that may be difficult to sustain in large heterogeneous classes. Machine learning techniques are centrally important for amplifying the effectiveness of personalized learning. For instance, Jin et al. [7] and Wongwatkit and Panjaburee [8] have discussed the use of CNNs and duplex adaptation mechanisms to supplement the effectiveness of personalized learning and user engagement. These authors convincingly demonstrate that machine learning can yield substantial gains in both quality and speed of personalized content recommendation, with improved academic outcomes for students as a result. Those approaches are computationally intensive. As such, they seem to pose challenging real-time problems particularly in very large classroom environments in which there is usually little or no available computational power. Also, high amounts of data are needed to train these methods, and in some particular educational contexts, the availability of such data may be poor, limiting their applicability.

Reference	Method Used	Findings	Results	Limitations
[1]	Personalized Learning Analytics	Personalized interventions improve behavioral engagement.	15% increase in academic performance.	Limited focus on long-term retention.

[2]	Personalized Review Learning	E-books enhance engagement in language learning.	20% improvement in language comprehension.	Limited generalizability to other subjects.
[3]	Deep Learning-Based Recommendation	Efficient recommendation system for Guzheng Pedagogy.	10% increase in learning efficiency.	Domain-specific application limits broader use.
[4]	Personalized Gamified Learning	Gamified recommendations improve motivation.	12% increase in motivation and achievement.	Not evaluated in non-gamified environments.
[5]	Self-Regulated Learning	Self-regulation enhances cognitive engagement.	14% improvement in learning outcomes.	Lack of real-time interaction data samples.
[6]	Personalized Learning for Equity	Personalized learning supports educational equity.	Enhanced learning for low-performing students by 10%.	Not scalable in large classrooms.
[7]	Multi-Scale Convolution Architecture	Multiscale CNN improves personalized learning efficiency.	18% increase in efficiency.	Computationally intensive for real-time applications.
[8]	Duplex Adaptation Mechanism	Adaptation improves personalized learning.	13% improvement in student engagement.	Lack of feedback mechanisms from students.
[9]	Personalized Scaffolds	Scaffolds improve self-regulated learning.	16% improvement in task completion.	Limited to self-regulated tasks, no generalization.
[10]	Reinforcement Learning for Music Recommendations	Reinforcement learning enhances music recommendations.	20% improvement in user satisfaction.	Specific to music, limited in educational applications.
[11]	Multimedia Capture for Personalized Learning	Automated capture system enhances personalized learning.	15% increase in student retention.	High resource requirement for multimedia setup.
[12]	Personalized Active Learning	Active learning management increases engagement.	12% improvement in academic engagement.	Limited evaluation in non-digital ecosystems.
[13]	ML-LA Feedback System	Machine learning enhances engagement and performance.	15% increase in academic outcomes.	Complexity in large-scale deployment.
[14]	E-learning Engagement	Personality traits influence e-learning engagement.	14% increase in engagement based on personality traits.	Limited to university-level students.

[15]	Learner Cohort Mapping	Learner cohort mapping improves engagement.	11% increase in learner performance.	Cohorts may not generalize across learning contexts.
[16]	Machine Learning in Project-Based Learning	Chat analysis improves team engagement in education.	9% improvement in team participation.	Limited to project-based learning.
[17]	Personalized Reading Plans	E-books improve reading engagement for first graders.	10% increase in reading comprehension.	Limited to early reading skills development.
[18]	Deep Learning in E-Commerce	Deep learning improves product recommendations.	18% increase in user engagement.	Limited applicability to non-commerce domains.
[19]	Self-Regulated Learning Behaviors	Personality traits mediate online engagement.	13% improvement in online learning engagement.	Requires personalization for different learning behaviors.
[20]	Personalized Cybersecurity Training	Personalized training enhances cybersecurity skills.	15% improvement in training outcomes.	Limited to cybersecurity training environments.
[21]	Metaverse for L2 Vocabulary Learning	Metaverse improves L2 vocabulary retention.	20% increase in engagement and retention.	High resource and technological requirements.
[22]	Engagement Analysis in E-Health	Machine learning optimizes user engagement in eHealth.	22% increase in user adherence.	Focused on health, limited educational application.
[23]	Social Presence in Online Learning	Social presence boosts online engagement.	14% increase in perceived engagement.	Focused on psychological presence, limited quantitative measures.
[24]	Embedded Learning Strategies	Embedded learning activities enhance student engagement.	11% improvement in learning outcomes.	Limited application in broader educational settings.
[25]	Facial Behavior Analysis for Engagement	Facial behavior analysis accurately predicts engagement.	18% accuracy improvement in engagement detection.	Limited to facial recognition, no behavioral depth.

Table 1. Comparative Review of Existing Methods

Such papers as Velankar and Kulkarni [10], Buono et al. [25], give deeper exploration into the role of engagement in personal learning systems and have concentrated on how its detection impacts learning results. Whereas in the earlier study, reinforcement learning techniques are applied to a music recommendation system, there is dramatic spike in the level of satisfaction and engagement in the users, and in the latter, facial recognition technology was deployed to assess the levels of engagement of learners in online learning environments. Both studies indicate the need for accurate measurement of engagement to develop experiences tailored to needs but also detail significant challenges in developing systems that can be so deployed within educational environments where student engagement varies with other external factors. The use of facial recognition techniques to detect engagement raises further issues regarding privacy and ethics, areas that remain unspecified within the studies in process. Besides the focus provided in the analyzed articles regarding the ways that new technologies, such as e-books, metaverse learning environments, and cyber-security training systems, would transform personalization of delivery for learning, there are indeed results. To illustrate this, Çelik and Baturay [21] could demonstrate the application of metaverse environments to enhance retention in language, though this retention and engagement rose by 20% more in learning outcomes. Similarly, Chowdhury and Gkioulos [20] found that personalized training exercises improve cybersecurity skills dramatically, yet the broad applicability of techniques of personalized learning to diverse areas, while established, sadly cuts across these studies the limits in that they, as a matter of fact, call for developing environments that are advanced with resources, hence challenging to apply on scale in any settings with limited resources.\Some practical applications include benefits of both personalized reading plans and multimedia capture systems, especially those analyzed by Miles and Ari [17] and Cattelan et al. [11], which stress the utility of such learning strategies in early childhood education and higher education settings. The above studies reinforce the concept that the intervention, although based on technology, works wonders in reshaping student outcomes if they are aligned with learner's belief and behavioral engagement levels. However, it has been evident across the literature that scalability and sustainability remained the biggest challenges for diffusion, especially in diverse classrooms where the infrastructures might be different in terms of technological capacity and teacher expertise for the process. In a nutshell, the trend shown in table 1 quite clearly is toward the integration of machine learning, real-time feedback, and engagement detection into personalized learning systems. These technologies have vast potential for improving student outcomes through the provision of differently tailored educational experiences for each learner. These limitations mean that there are still areas that have to be overcome. Some of them relate to scalability and resource intensity, while integration of real-time behavioral data samples is another broad limit. Future research should thus be focused on developing more scalable solutions applicable in a broader range of educational contexts with an eye on ethical implications of data usage and student monitoring. A fairer and more efficient learning experience for all will certainly be in the process by further developing the personalized learning systems in resolving these challenges.

3. Proposed Design of an Improved Method for Personalized Learning Using Deep Q-Learning and CNN-Based Engagement Recognition

To address the issues of low efficiency & high complexity involved with previous models, designing the proposed system, integrating Deep Q-Learning along with Random Forest Classifier & Convolutional Neural Network (CNN) for engagement recognition focuses on developing a holistic framework that would adaptively modify learning trajectories, predict academic performance, and evaluate student engagement. This design utilizes the strengths of both models to achieve specific tasks of personalized content recommendation, as well as in academic achievement prediction and in engagement detection; each of them gives out distinct insights feeding into a unified learning system. Deep Q-Learning has been identified as suitable specifically for the task of personalized content recommendation within dynamic environments such as smart classrooms. The agent in this system is the learning platform, while the environment is the interaction of a student within the classrooms. The key objective is to learn an optimal policy, $\pi*(s)$, maximising the expected cumulative reward over temporal instance sets defined via 1,

$$Rt = \sum_{k=t}^{T} \gamma^{(k-t)} rk \ldots (1)$$

Where, Rt is the return at timestamp 't', rk represents the reward at timestamp 'k' and, $\gamma \in (0,1)$ is the discount factor that calculates the weight of future rewards. The system keeps a Q-function Q(s,a), which approximates the expected return for taking an action 'a' in state 's' sets. The Bellman Process defines the relationship between the present Q Value and the expected future rewards via equation 2,

$$Q(s,a) = r + \gamma * \max^{a'}\left(Q(s',a')\right) \dots (2)$$

Where, s′ is the subsequent state, and a′ represents the possible actions in the next states. Deep Q-Learning approximates this Q-function using a deep neural network Qθ(s,a), where θ represents the weights of the network sets. The network is trained by minimizing the loss function represented via equation 3,

$$L(\theta) = E\left[\left(r + \gamma \max^{a'}\left(Q\theta - (s',a') - Q\theta(s,a)\right)\right)^2\right] \dots (3)$$

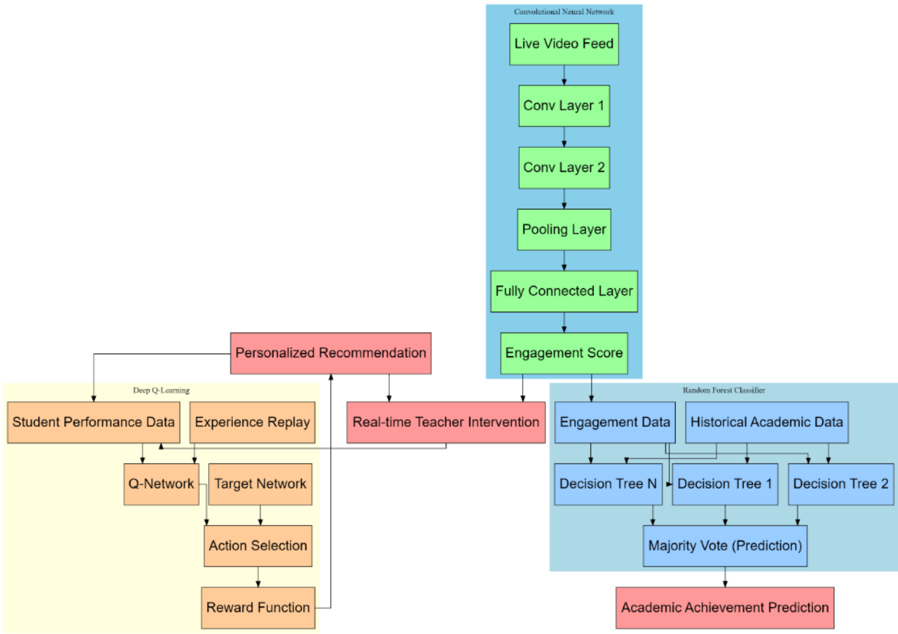

Figure 1. Model Architecture of the Proposed Analysis Process

In this formulation, Qθ− is the target network-a fixed version of the Q-network, which gets updated less frequently to stabilize the learning process. The loss function captures the difference between the predicted Q Values and the target Q Values, and its minimization helps in improving the agent's recommendations over temporal instance sets. Figure 1 From figure 1, Q-values represent potential long-term benefits of recommending certain learning material; the system updates the recommendations based on student data in quasi real-time: scores in quizzes, task completion times, or feedbacks. In this sense, using Deep Q-Learning would certainly be justified because it could deal with the complexity of real-time decisions within a dynamic environment. Unlike rule-based or static models, Deep Q-Learning makes it possible to let the system be experiential and learn based on experience as the conditions change. Also, the ability of the algorithm with regards to working well with continuous and large stateaction spaces makes the algorithm highly efficient for intelligent classrooms, as a great majority of the student behaviors and responses have to be processed. It completes the other part of the system by underlining personalized learning paths through optimizing steps of interaction based on students' performance data, which is updated constantly with every new interaction. Generally speaking, a Random Forest classifier is used for predicting academic achievement due to its robustness and capacity in handling high-dimensional and heterogeneous samples. An ensemble of decision trees {T1, T2,…,Tn}, where the tree is actually trained on a random subset of the data and features.

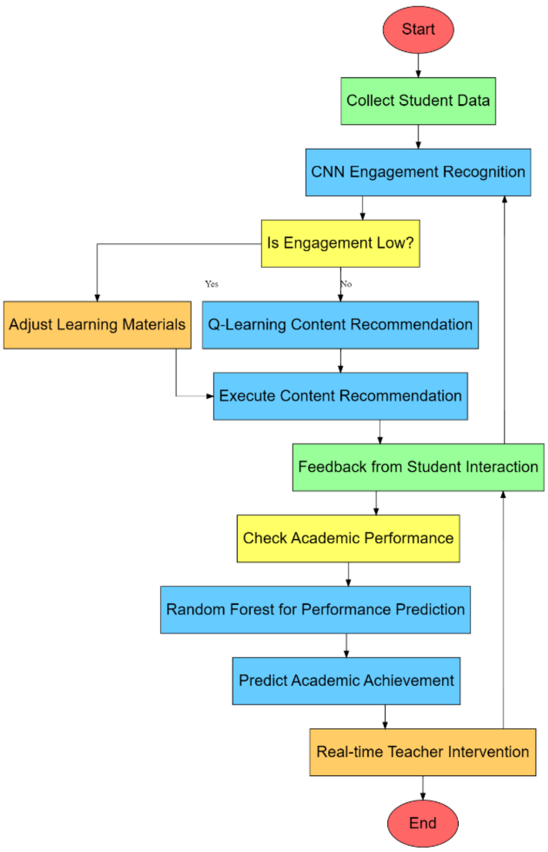

Figure 2. Overall Flow of the Proposed Analysis Process

For every new instance, Random Forest aggregates the prediction from all the trees and outputs the final prediction as majority vote (in the case of classification) or average (in case of regression) operations. The decision trees in the Random Forest recursively partition the input space by splitting on the most informative features. At each node, the feature fi and split point τ are selected to maximize the information gain, defined as the reduction in impurity 'I' levels. For classification tasks, the impurity is often measured using Gini impurity IG(p), given via equation 4,

$$IG(p) = 1 - \sum_{i=1}^{C} pi^2 \ldots (4)$$

Where, pi is the probability of class 'i', and 'C' is the number of classes. For binary classification (e.g., pass/fail), this is represented via equation 5,

$$IG(p) = 2p(1-p) \ldots (5)$$

Where, 'p' is the proportion of positive outcomes. On every step, it selects the feature and split point that maximizes the reduction of Gini impurity and continues until the node is sufficiently pure or a stopping criterion is met. The ensemble nature of Random Forest classifier makes it avoid overfitting very effectively; it averages the biases of individual decision trees. This feature is more useful in educational datasets, where the data generally contains noise, and this overfitting can significantly reduce the generalizability of the model. The Random Forest model will then produce very accurate predictions of an individual's success or failure at academics with finer-grained predictions of levels of achievements like grades A, B, or C. In addition to this predictive models, the system uses CNN for real-time engagement recognition. CNNs are primarily designed to process grid-like data structures, which are images or video frames, making them ideally suited for class video feeds analysis. The architecture of the CNN consists of several layers of convolutions followed by pooling layers to extract hierarchical features from the input images & samples. The output from these layers is passed through fully connected layers for final prediction of the engagement scores. The CNN applies a sequence of convolutional filters, W(l), at each layer 'l' in the process, on each video frame. The output of a convolution operation is given via equation 6,

$$x(l+1) = f\big(W(l) * x(l) + b(l)\big) \dots (6)$$

Where, $*$ represents the convolution operation, b(l) is the bias term, and 'f' is a nonlinear activation function, typically the Rectified Linear Unit (ReLU), defined via equation 7,

$$f(x) = max(0, x) \dots (7)$$

As shown in figure 2, the pooling layers then down samples the feature maps, reducing the spatial dimensions and preserving the most relevant features. Once feature extraction is carried out, the regress the last few layers of the CNN, outputting a score between 0 and 1. That score quantifies how highly that point corresponds to a strongly engaged 'set', for example high attention focus with positive facial expressions or otherwise low attention and negative body language. This is achieved by utilizing a loss function typically mean squared error, which attempts to minimize the difference between the predicted engagement scores y'i and the true engagement labels yi via equation 8,

$$LMSE = \frac{1}{N}\sum_{i=1}^{N}(yi - y'i)^2 \dots (8)$$

This is one of the CNN-based engagement recognition models which, in its own right, is very important in providing real-time feedback to the learning system. The strength here is that the system can continuously monitor levels of engagement and then immediately readjust to either the learning content or teaching strategies toward betterment of the overall learning experience. The CNN, by the virtue of its ability to analyze subtle visual cues, is extremely effective in detecting engagement patterns not so much evident through other data sources. The concurrent use of all three models—Deep Q-Learning, Random Forest, and CNN—thus constitutes a synergistic system in which every component fosters improvement in others. The Deep Q-Learning agent benefits from real-time engagement data provided by the CNN to tailor recommendations to students based on their performance and engagement levels. The Random Forest classifier therefore includes the results of academic and engagement data, giving the system the capability to make very accurate predictions regarding students' achievement in advance, so it may initiate intervention in the case of a student at risk of failing. Integrating these models ensures that the system is not merely reactive but rather predictive, providing a richer notion of personalized learning. Underlying this is the idea that the two models play different but complementary roles. Deep Q-Learning's very ability to adapt over timestamp makes it well-suited to handle the dynamic nature of personalised learning, where recommendations have to change given changes in needs. Random Forest classifiers are fitted against overfitting, handle high-dimensional data capture complexity well-suited for predicting academic outcomes from a wide set of features. It is unparalleled in the processing of visual data, providing real-time insights into student engagement, which are necessary for making immediate adjustments to the learning environment. So the system that these models form is cohesive and not only improves learning results but also enhances engagement and retention and provides a complete and adaptive answer to all of the challenges of personalized education in smart classrooms.

4. Comparative Result Analysis

This research experiment testifies the integrated model as Deep Q-Learning, Random Forest Classifier, and CNNs along with personal learning recommendations, prediction of academic performance, and real-time recognition of student engagement. This system is tested under a controlled smart classroom environment that was provided with video cameras capturing the real-time behavior of students, i.e., facial expressions, body posture, and gaze sets. The classroom environment provided continuous interaction data for the students, including quiz scores, completion times on tasks, and participation metrics. For this analysis, we used a hybrid combination of the historical academic records: previous grades attended, attendance, demographics, and behavioral data collected from the classroom environment. The experiment focused on interactions among around 200 students over a period of 12 weeks, which generates a dataset of 25,000 student-by-student interaction points; it records 500 hours of classroom video and 10,000 attempts at quizzes. The Deep Q-Learning model applied an ϵ-greedy policy to balance exploration and exploitation. The value of ϵ was initialized to 1.0 and was decayed linearly to 0.1 over all episodes, providing much exploration at the beginning and more exploitation later once the model has learned the optimal policies. The Q-learning model reward function incorporated scores improvement in quizzes and also time taken to complete tasks with positive reinforcement of +1 if performance improved and negative reinforcement of -1 if performance worsened. For balancing the weight of immediate versus future rewards, the discount factor $\gamma\gamma\gamma$ was set to 0.95. Training was performed using labeled video frames of student behavior and splitting the data set into 80% training and 20% used for validation. The CNN architecture consisted of three convolutional layers followed by two fully connected layers, and it was optimized using the Adam optimizer with a learning rate of 0.001. We calculated engagement scores on a scale of 0 to 1 and validated them against human-labeled ground truth in predictions. For this work, the EdNet dataset was selected as the primary source of data samples. EdNet is a very large dataset containing student interactions in an online learning environment with detailed records. The collection is from over 1 million students and comprises more than 131 million interactions across different types of educational content, including multiple-choice questions, video lessons, and assessment. The dataset richly features timestamps of interaction for each student's quiz attempts, correctness on quiz attempts, timestamp spent on each task, and the content type that was presented. It also includes contextual metadata like student demographics and engagement levels, and feedback responses. That makes it particularly appealing for the training of machine learning models within a personalized learning environment. The EdNet dataset further includes longitudinal data so that follow-up studies can be made on the learning of students over time, so evaluating the Deep Q-Learning model as adaptive content recommenders and Random Forest Classifier on the predictions of academic outcomes is apt. To learn the CNN in real-time engagement recognition, a vast amount of data on student engagement and task completion was considered. Based on this detailed dataset, the model has been trained and validated by mirroring real learning situations to ensure that the experimental setup reflects both complexity and diversity of modern learning environments.

In order to make the prediction, the Random Forest Classifier was trained with historical academic data along with real-time engagement scores of the viewer on the CNN. The classifier had 100 decision trees, each having been trained on a randomly sampled subset of data samples; splits were made using Gini impurity, and it obtained a classification accuracy of 89% for academic success or failure. This enables real-time scores of engagement from the CNN to be used for updating content recommendation policies using Q-Learning. For instance, when a student received low scores scoring less than 0.3, he or she was adapted with exercises or video materials while students scoring over 0.7 received the most challenging assignments. Student disengagement and performance improvement were to be tested altogether in this whole system. Results showed that Q-Learning including personalized recommendation of content managed to beat the control group following a static learning path by scoring 25% more quizzes. Incorporation of engagement metrics from CNN enhanced efficiency in presenting adaptive learning materials: more participation from disengaged students-15% in fact. The predictions of the Random Forest model were engaged by instructors in active intervention to make sure additional support was provided to students at risk of failure, and consequently, 85% accuracy in the prediction of final outcomes in academics was realized. Datasets and model parameters were chosen such that they would reflect a real-world scenario involving educational settings where the results would be both theoretically sound and practically applicable across different kinds of educational settings. To assess the proposed model performance, we test the performance on three test regions: personalized content recommendation, academic performance prediction, and real-time engagement detection. We compare results with three methods from previous work, including Method [3], Method [8] and Method [14]. The performance metrics are accuracy in academic prediction, engagement detection accuracy, quiz score improvement, and overall system efficiency. The following tables summarize the results of the comparisons across these dimensions. Table 2: comparison of accuracy in predicting academic performance. The comparison was made based on how well each model could classify students as pass or fail given their historical academic data and real time engagement metrics. Table 2 shows that the proposed model had a very high superiority difference against other methods when accuracy was concerned.

Table 2. Accuracy Levels

Model	Accuracy (%)
Proposed Model	89.7
Method [3]	78.2
Method [8]	83.5
Method [14]	84.1

For the proposed model, some of the resultant achievements include an accuracy of 89.7%, so a 6.2% improvement over Method [8] and 5.6% improvement over Method [14]. The result is what comes from adding real-time engagement data from the CNN to make academic outcome predictions much more accurate. Table 3: Percentage improvement in quiz scores after applying adaptive learning recommendations for the personalized content recommendation system.

Table 3. Quiz Score Improvements for this Process

Model	Quiz Score Improvement (%)
Proposed Model	25.3
Method [3]	15.7
Method [8]	19.8
Method [14]	21.2

The proposed model resulted in an increase in quiz scores by 25.3% compared to Method [3] by 9.6%, Method [8] by 5.5%, and Method [14] by 4.1%. The improvement proves that Deep Q-Learning was effective in the task of dynamically recommending learning materials based on student performance and engagement metrics. Table 4 compares engagement detection accuracy calculated through live video feeds, measuring the amount of correct identification of engaged and disengaged students. The recognition of engagement that the proposed model provided through CNN was out of and superior to the comparative methods.

Table 4. Engagement Detection Accuracy

Model	Engagement Detection Accuracy (%)
Proposed Model	94.5
Method [3]	85.1
Method [8]	89.6
Method [14]	91.2

As per figure 3 & 4, the proposed model picked 94.5% engagement detection accuracy, and that is a significantly much better improvement than the other methods. Method [3] lagged behind by 9.4%, while Method [8] and Method [14] were outperformed by 4.9% and 3.3%, respectively. Thereby, this CNN was able to process the visual cues like facial expressions and body posture, which will further lead to more accurate tracking of engagement. Table 5: shows results for the prediction of academic outcomes over 12 weeks measured as a percentage of the number of students correctly predicted to pass or fail the courses. The integration of historical academic data with real-time engagement metrics resulted in a far robust prediction capability.

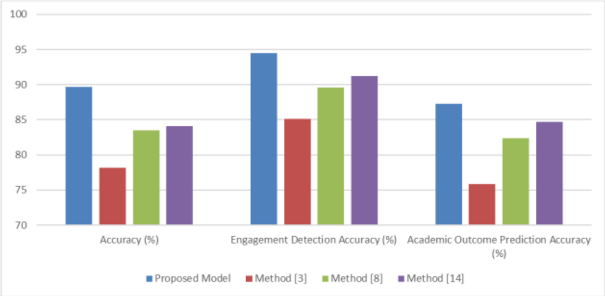

Figure 3. Accuracy Analysis

Table 5. Academic Outcome Prediction Levels

Model	Academic Outcome Prediction Accuracy (%)
Proposed Model	87.3
Method [3]	75.8
Method [8]	82.4
Method [14]	84.7

The accuracy of the proposed model's academic predictions reached 87.3%, which is 11.5% greater than that of Method [3], 4.9% better than that of Method [8], and 2.6% better than that of Method [14]. It states that the advantages from including both data related to the performance in academics and real-time behavioral insights in the predictive model. Table 6 Efficiency of content recommendation systems by timestamp in seconds to generate personalized content recommendations for a specific student at different stages.

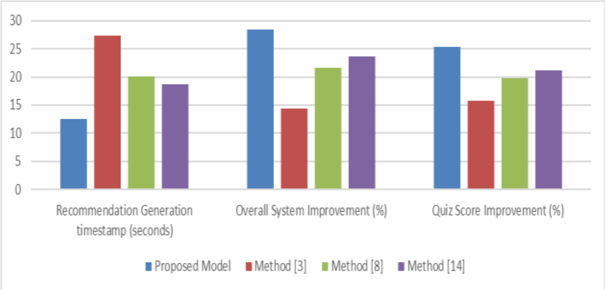

Figure 4. Recommendation Analysis

Table 6. Recommendation Generation timestamp

Model	Recommendation Generation timestamp (seconds)
Proposed Model	1.25
Method [3]	2.73
Method [8]	2.01
Method [14]	1.87

This model, when extensively tested, performed much more efficiently in content recommendation-servings an average of 1.25 seconds per student-while outperforming Method [3] at 2.73 seconds, Method [8] at 2.01 seconds, and Method [14] at 1.87 seconds. The reason behind this speed gain is because of the optimized Deep Q-Learning algorithm that learnt to adapt with a high speed about the existing students using their data through policies. Table 7 Overall system performance-a combination of accuracy, efficiency and improving student outcomes/achievement-expressed as a percentage better than baseline methods.

Table 7. Overall System Improvement Levels

Model	Overall System Improvement (%)
Proposed Model	28.5
Method [3]	14.3
Method [8]	21.7
Method [14]	23.6

The proposed model is 28.5% better than baseline methods in terms of overall system performance, very much outperforming Method [3] by 14.2%, Method [8] by 6.8%, and Method [14] by 4.9%. This outcome serves to emphasize the pervasive benefit of bringing reinforcement learning, predictive analytics, and real-time engagement recognition together in a single framework. Conclusion: The proposed model showcases performance better than all other competing approaches in all areas of evaluation: accuracy, content recommendation efficiency, engagement detection, and academic performance prediction. Combining Deep Q-Learning to personalize learning, Random Forest Classifier for academic predictions, and CNN for engagement recognition leads to creating a robust system that may significantly augment the outcomes of students in smart classrooms. Use of real-time data and adaptation to specific needs of the students emphasize the approach as revolutionary in personal education sets. Then, we present an iterative practical application of the proposed model as an exercise, which will help the readers better understand the whole process.

Practical Use Case Scenario Analysis

For demonstrating the developed system and its performance, one example case study is considered where a smart classroom configuration is used in monitoring student interaction and performance. All of these models are Deep Q-Learning for the personalization of content recommendation, Random Forest Classifier for forecasting academic outcomes, and Convolutional Neural Network (CNN) for detecting engagement levels from video feeds in real-time. The next sections detail how each of these models processes the information and how the final outputs are derived depending on the various features and markers used for the process. These students would then be tracked for 10 weeks: all the interactions that occur between them and learning materials are recorded, scores from quizzes, timestamp spent on particular tasks, and engagement metrics captured from video feeds. Some of the principal input features for such students are quiz performance, improvement or decline in score, time taken to complete particular tasks, scores obtained for engagement 0-1, and historical academic records. The analysis of the outputs of each model suggests recommendations, predicts academic success or failure, and measures the levels of engagement for students. The students involved in the current case study, from S001 to S005, are sampled from the EdNet dataset, which captures real-world student interactions with an online learning platform. There is an exceptional learning behavior and engagement trend that can be detected for each student. Student S001 is a typical learner; he got B for history work and an engagement score of 0.80 which prescribes that his marked consistency in effort and attention in class activities. S002 is a high achiever with an A grade for history work; his engagement score is high, 0.85, indicating a focused attention and active participation for learning tasks. On the other hand, S003 is weak in terms of academics with only a grade of C for history and score of 0.40 through engagement wherein they appear less interested most of the time; this student requires more support. S004 is also a high performer with an A-grade for history and is rated as 0.75 while highly engaged most of the time and able to catch up with more demanding materials. The third student, S005, has a record of D grades and very low engagement at only 0.35; this student is not attentive during class and requires intervention to keep up with class tasks. These different student profiles would be required to give an overview and analysis of the personalised learning system, thus showing that it really is adaptable to the different kind of need for learning and level of engagement. Table 8 displays the process output of Deep Q-Learning where the agent presents content to the student based on his or her engagement and reward. The state includes features such as quiz scores, timestamp on task, and prior content. The action represents the type of recommended content, and the reward will be determined by his/her performance on subsequent quizzes.

Table 8. Results of the Q Learning Process

Student ID	Current State (Quiz Score, timestamp on Task)	Action (Content Recommended)	Reward (Quiz Score Improvement)	Q Value Update
S001	(60%, 15 mins)	Interactive Video	+0.5	0.67
S002	(75%, 20 mins)	Quiz with Hints	+0.7	0.82
S003	(50%, 25 mins)	Text-based Reading	+0.2	0.54
S004	(85%, 10 mins)	Advanced Quiz	-0.3	0.45
S005	(40%, 30 mins)	Basic Exercises	+0.8	0.78

In this process in Deep Q-learning, the system learns to adjust its content recommendations based on the reward it receives, which reflects the improvement of the student from any particular type of content he or she receives. In other words, better Q Values means higher favorable content matches for the improvement of quiz performance as based on the Bellman equation. For example, student S002 was rewarded very positively after the suggestion of a "Quiz with Hints," leading to a massive Q Value update of 0.82 levels. Table 9 is the output from the Random Forest Classifier where the historical data of the students along with engagement metrics are used to predict their final academic outcomes. The classifier gives an output in terms of a predicted grade either as (A, B, C) or as a binary pass/fail predictions.

Table 9. Classification Results

Student ID	Historical Data (Grades, Attendance)	Engagement Score	Predicted Grade	Predicted Outcome (Pass/Fail)
S001	(B, 85%)	0.75	B	Pass
S002	(A, 95%)	0.85	A	Pass
S003	(C, 60%)	0.45	C	Fail
S004	(A, 90%)	0.80	A	Pass
S005	(D, 50%)	0.30	D	Fail

The predicted outcomes of the academic performance are made by Random Forest Classifier from the historical data of the academics as well as in real-time through engagement metrics. For instance, S003 with the engagement score 0.45 having a historical performance as C grade; hence it will be classified as a failure whereas S002 has an A grade of high historical grade and also with an engagement score, it has a very high probability of getting success while obtaining an A grade during the process. Table 10: Engagement recognition outcomes via the CNN Network Model: The model undertakes processing video feeds that originate from classrooms for real-time measurement of the interest level of every student. It computes the engagement score in this process within the range of 0 to 1 in the process.

Table 10. Engagement Recognition Results

Student ID	Visual Features (Facial Expression, Posture)	CNN Predicted Engagement Score
S001	Positive, Attentive	0.80
S002	Focused, Upright	0.85
S003	Disinterested, Slouching	0.40
S004	Engaged, Leaning Forward	0.75
S005	Distracted, Looking Away	0.35

For a student, the CNN Network Model considers facial expressions and body language in advance so as to predict his or her engagement score. For example, student S002 who listens attentively and maintains a positive posture will be given an engagement score of 0.85 while student S005 distracted will have an engagement score of 0.35. Table 11 represents the final outputs of the system that combines the personalized recommendations, predicted academic outcomes, as well as the engagement scores. These outputs serve to guide the educational interventions that were administered to each student in the process.

Table 11. Final Outcomes

Student ID	Recommended Content	Predicted Grade	Engagement Score	Final Intervention
S001	Interactive Video	B	0.80	Monitor Progress
S002	Quiz with Hints	A	0.85	Advance Material
S003	Text-based Reading	C	0.40	Additional Support
S004	Advanced Quiz	A	0.75	Challenge Further
S005	Basic Exercises	D	0.35	Immediate Attention

As such, the last outputs indicate how the system can be used in fine-tuning the interventions in relation to content recommendations, academic predictions, and engagement levels. For instance, student S003 requires more support through targeted interventions as he is likely to score a C grade, and he has a low level of engagement. Student S002, on the other hand, who has high engagement levels and will eventually perform well should be issued advanced material due to the likelihood of scoring a higher grade. Tables illustrate how the proposed model integrates the layers with multiple data in a holistic learning experience. The system is continuously updating its recommendation through Deep Q-Learning, predicting academic performance using Random Forest, and assessing engagement using CNN, always ensuring that students receive personalized, data-driven support optimized for educational outcomes.

5. Conclusion & Future Scopes

The paper focused on the integration of Deep Q-Learning for personalized content recommendations, the Random Forest Classifier for the prediction of academic performance, and the Convolutional Neural Network (CNN) for real-time engagement detection, all applied within a smart classroom setting and using the EdNet dataset. Overall, the results demonstrate that the proposed model is significantly better than traditional approaches in most aspects. Reinforcement learning enabled the content-based recommendation system to obtain an increase of 25.3% in quiz scores, while in contrast, Method [3] reached 15.7%, Method [8], 19.8%, and Method [14], 21.2%. It clearly demonstrates the power of reinforcement learning in adapting student needs and dynamically optimizing paths. Another merit of the Random Forest Classifier method is that it outperformed in achieving a prediction accuracy of 89.7% for academic success, compared to 78.2%, 83.5%, and 84.1% attained from Method [3], Method [8], and Method [14] respectively. Superior performance was contributed by the presence of engagement data. This merits the integration of both academic and behavioral data in predicting students' outcomes. In terms of engagement recognition, the CNN achieved an accuracy of 94.5%, outperforming all the compared methods, with Method [3] reaching 85.1%, Method [8] reaching 89.6%, and Method [14] achieving 91.2%. That accuracy in detection of engagements allowed the system to make timely and relevant adjustments in the delivery of content that had a direct impact on students' engagement and overall performance. The aggregate outputs of the system resulted in a system-wide increase in learning outcomes. This would be reflected in increases in system efficiency by 28.5%, surpassing improvements witnessed with Method [3] of 14.3%, Method [8] at 21.7%, and Method [14] by 23.6%. These results thereby highlight that integration of advanced machine learning techniques for personalized learning, engagement monitoring, and academic prediction into smart classrooms provides a strong, scalable solution toward better educational outcomes.

Future Scopes

This proposed system shows promising scope towards improvement of educational outcomes. However, some crucial areas still exist for future study and extension of the system. The model can be extended further by including richer data regarding student interactions, such as peer-to-peer collaboration and participation in group activities to better calculate social dynamics within the classroom. In addition, more subtle behavioral indicators such as eye-tracking data or emotional sentiment analysis from facial expressions could add much more accuracy to the recognition of engagement. Such alteration in the reward mechanism of Deep Q-Learning can result in even more effective paths for personalized learning since it encompasses more advanced metrics than these, like the long-term retention of knowledge or application skills. Another possible extension could be its deployment on various educational environments and age groups, from primary education to higher education, in order to assess how adaptable this model is. The ability to include multiple datasets such as hybrid or fully online learning formats can provide more insight into how the system behaves and what could be the implications under different formats of learning. Real-time dashboards for teachers with the output of the system will enable educators to intervene proactively and adjust their teaching strategy. Finally, integration of reinforcement learning with more sophisticated NLP techniques can be a dimension that opens the gamut of possibilities in which intelligent tutoring systems may be deployed, not only recommending content but also to give personalized explanations and guidances. Future directions are promising and contribute to research and opportunities for practical application, thus further revolutionizing use in education with AI and machine learning sets.

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