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Lightweight CNN-RL Adaptive Feedback for Gamified Learning Platforms: A Review

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Abstract

The rapid increase in online and blended learning has added pressure on the necessity to have adaptive, engaging, and efficient educational technologies. This paper provides a review and syntheses of the current developments in lightweight convolutional neural networks (CNNs) and reinforcement learning (RL) to support the establishment of real-time, personalised feedback in a gamified learning setting. The paper presents the theoretical premises, system designs, and experimental findings of the recent designs, and emphasises the potential and difficulties of implementing these systems to resource-constrained platforms. As we have shown in the analysis, the combination of lightweight CNNs with RL agents can allow adaptive learning to become scaled, responsive, and efficient, and become the foundation of the intelligent education platform of the next generation.

Keywords: *Adaptive Feedback, Convolutional Neural Networks, Gamification, Learning System, Reinforcement Learning*

1. Introduction

Personalized learning and gamification have revolutionized education, providing customized learning experiences that enhance engagement and learning outcomes. But providing real-time and adaptive feedback is still a big challenge, particularly on low end devices. There is a common problem that traditional deep learning models are too expensive to deploy them in the classroom or students' personal device [1][2]. However, the model exhibited poor efficiency in terms of storage space and prediction speed [1] although its performance in image recognition was high.

Most important, these restrictions will impact the overall model performance; thus, requiring a solution that would achieve accuracy and efficiency simultaneously. To address this, recent studies have been targeted at lightweight convolutional neural network (CNN) architectures and efficient reinforcement learning (RL) algorithms, which can be used to adapt to individual learner states in real time on-device [3]. While maintaining the models' accuracy, it is essential to reduce the model's size and computational resources.

2. Related Works

2.1 Lightweight Convolutional Neural Networks (CNNs) for Efficient Perception

This study introduces the Lightweight Convolutional Neural Networks (CNNs), which are utilized for efficient perception. In order to save the computing resources, lightweight CNNs like depthwise separable convolution and binarized weight CNNs are also built to achieve very high accuracy. They are especially well suited for mobile and embedded applications, and are ideal for educational settings that have limited hardware resources. In short, the idea of compression has been employed to enhance the space and speed efficiency of CNN. It was used on the model architecture and/or weights to decrease the number of parameters of the network. In addition, CNN which has been developed recently was to increase the performance of the network by reducing the

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number of network parameters. Some lightweight CNN methods, according to [1] include: SqueezeNet, MobileNetV1, MobileNetV2, ShuffleNetV1, MixNet, and EfficientNet

2.2 Reinforcement Learning (RL) for Adaptive Feedback

For the provision of adaptive content delivery and feedback in e-learning platforms, RL, particularly Deep Q-Networks (DQN) and Policy-Gradient have been used widely. RL agents learn the best pedagogical strategies to maximize accumulated rewards based on student engagement and student performance [1]. Some recent techniques are Markov Decision Processes (MDP) and feedback efficient algorithms that require minimal human input [3] to do so. The adaptive feedback will be a stochastic control problem, in this case, Markov Decision Process (MDP), whose state of the environment will be determined through the student's interaction with the learning platform. Some interactions influenced by platform and some random.

The MDP problem is practically solved using function approximation or deep reinforcement learning due to the curse of modeling and curse of dimensionality issues and optimally solved using dynamic programming [4].

2.3 Gamification and Engagement

In the current learning context, especially in the traditional classroom, the utilization of game design elements, such as badges, points, leaderboards and progress bars, in a non- game context is called gamification [5]. It guarantees a higher leaner engagement with improved learning outcomes. These gamified features are integrated with adaptive feedback to keep players motivated and motivated to learn [3]. Research has demonstrated that these integrations are associated with better academic results and satisfaction, especially for pupils with initial difficulties [3].

3. Methodology

3.1 Integrated CNN-RL Frameworks

Current adaptive learning systems combine light-weight CNNs that process the learners' current perceptual state (such as facial expressions, behavioral logs) with RL agents that generate the adaptive feedback actions [2]. These systems can dynamically control the difficulty of the content, its presentation style, and feedback, because of the multimodal data, so that the learning efficiency and satisfaction will be better [1]. The architecture of an adaptive personalized platform for an effective and advanced learning is presented in Figure 1.

Based on the reviewed studies, most of the studies have included only the adaptation means with rule-based adaptation (RB) strategy [6] but the development of a hybrid model is shown to have better user experience with adaptive feedback.

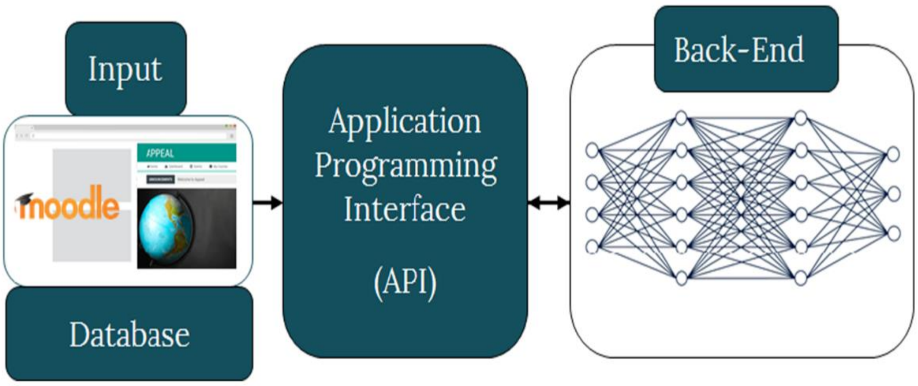

Figure 1: Adaptive Personalized Platform for an Effective and Advanced Learning (APPEAL) [3]

4.0 Empirical Review

According to a study by Zhou, Chen, Wang, and Huan [1] which used the ImageNet dataset, the six lightweight CNN models evaluated in this study based on ImageNet dataset yielded superior performance by tuning the optimization parameters to optimize the overall performance of the CNN model while preserving its accuracy and speed. In addition, lightweight CNN models were found to be stable when applied to different amounts of data and different levels of difficulty [7].

Sayed et al. [3] thus came up with an adaptive personalized platform for an effective and advanced learning (APPEAL) for school students. To engage the learners, particularly in the era of COVID-19, the authors suggested an adaptive gamified platform for personalized learning, in which Visual/Aural/Read, Write/Kinesthetic (VARK) presentation appeared. The purpose of the study was to enhance learning by making comparisons between the pre-test and post-test in a pilot study. The methodology used was the Deep Q-Network Reinforcement Learning (DQN-RL) and an online rule-based decision-making implementation method, so that the academic performance and satisfaction level of the VARK group had better improvement.

Tashtoush [8] suggested a study which demonstrated the correction of learning style with dynamic learner model. Not all types of adaptation strategies were, however, mentioned. In another study by Dolenc and Aberšek [9] considered dynamic feedback of the model was emphasised in the developed system. Learning style used, however, was not investigated. Moreover, Chu et al. [10] presented a system which analyzed students' problem-solving process and gave individualized feedback adaptively to enhance students' learning. Based on the success of adaptive e-learning systems based on DQN-RL and lightweight CNNs on learning outcomes and engagement, fusing the computational power of the lightweight CNN-RL systems could provide real-time, personalized feedback with low latency and resource usage.

Therefore, most model-free reinforcement learning algorithms, like Q-learning algorithm, developed by using non-linear function approximators and fixed policy or off-policy learning, are divergent, while those developed by linear function approximators with better convergence guarantee [11] are convergent. To address the divergence problems with Q-learning, Mnih et al. [12] made an argument that deep neural networks have been used to estimate the environment with gradient temporal-difference methods that converge when used to evaluate a fixed policy with a non-linear function approximator [13] or when learning a policy of control with linear function approximation using an environment restricted version of Q-learning [14]. However, these techniques are not yet generalizable to the nonlinear control case.

Sankara [15] developed a personalized recommendation system with the aim to improve personal preferences for a better academic performance. The system used Hybrid Neural Recommendation Algorithm (HyNRA) that is a mixture of two methodologies Collaborative Filtering (CF) and Content Based Filtering (CBF) in a neural model and it was found that the result achieved a better student engagement over time. Also, to give real-time feedback based on students' engagement, Klein and Celik [16] developed a system that used a dataset that labelled student engagement based on behaviour and postures. He methodology used was AlexNet (based on a CNN) that performed better than Support Vector Machine approach. The outcome demonstrated the good performance of deep learning using a real-world image dataset.

In addition, Costa et al. [17] conducted a research to explore the relationship between gamification and artificial intelligence. The authors claimed that mathematical models gave a fundamental structure to optimize gamified systems, making them effective, sustainable, and personalized for users to ensure their engagement and experience, while also having the ability to continuously collect data and analyse them, which can be used to continuously improve the system and make it responsive to the needs and preferences of the users. For this reason, Jack, Alexander and Jones [18] conducted a research to analyze the effect of gamification on engagement in the statistics classroom. The result showed that the proper gamification strategies can have a positive impact on student motivation and engagement.

Gogawale et al. [19] used deep learning algorithms to build a multiclass multioutput deep learning model to identify attentiveness index of the learners using the computational power of deep learning algorithm. The model was based on used convolutional neural networks (CNN) and a publicly available dataset, DAiSEE was used for the model training and testing. The was necessary as only a few studies have tried to detect learners' attentiveness in online learning despite the advances in the use of deep learning techniques to enable the visual perception of machines.

To explore the effect of gamification on learner engagement, completion rates and satisfaction, Moldez et al. [20] conducted a study in a gamified learning system. To this end, Paiva et al. [21] created an open-source progressive web program for engaging experience in programming. This system used gamification and automatic assessment. The result from the study showed that it generated relevant instant feedback to the students. These are promising advances in recent years, but there is still a gap between the performance of the current lightweight CNN-RL systems and their performance in the real-world gamified learning context. Empirical studies have revealed positive results such as a lightweight model with an accuracy of 77.3% and with a reduced computational cost, increased engagement and academic outcomes with gamified adaptive feedback, and real-time content delivery of personalized content with minimal latency, however there are some significant challenges that have yet to be addressed.

The issues that were identified in the literature were: complexity-accuracy trade-offs, privacy issues and data security issues in multimodal learning systems, convergence issues of Q-learning with nonlinear function approximators and the absence of effectiveness of evaluation metrics in realistic classroom settings, and lack of research on multimodal learning data fusion techniques for comprehensive evaluation of lecturer states.

To tackle these gaps and enable the deployment in resource-limited educational environments, a multi-faceted solution framework is proposed, targeting to: 1) design more efficient optimization strategies that reduce the computational cost without compromising the accuracy of the prediction when applied to mobile and embedded learning systems; 2) design privacy-preserving deep learning architectures with differential privacy guarantees of sensitive learner data; 3) extend theoretical convergence guarantees of model-free RL algorithms to nonlinear control policies by means of advanced gradient temporal-difference methods; 4) design comprehensive, context-sensitive evaluation frameworks that capture quantitative metrics (learning gains, duration of engagement) as well as qualitative aspects (experience of the user, inclusivity across diverse learner groups); and 5) develop multimodal fusion techniques that seamlessly integrate visual, auditory and behavioral data streams for robust real-time learner state estimation.

5.0 Conclusion

The combination of lightweight CNNs and RL in gamified educational systems portrays a great enhancement in one-on-one learning. These systems can offer a scalable, efficient and effective solution for real-time adaptive feedback and may be the potential game changers for learning experience of various student populations. Although encouraging, there are still issues to overcome in order to balance model complexity versus accuracy, the privacy of data, and applicability to a wide range of educational settings.

Further efforts to minimise the computational overhead, improve multimodal data fusion, and design effective evaluation systems to apply to a real classroom should be the subject of future research. Furthermore, the development of these solution pathways should be designed in such a way that large-scale classrooms pilot studies of diverse educational settings and populations are included to examine the generalizability and sustainability of CNN-RL adaptive systems in real learning environments.

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