An Intelligent E-Learning Framework for Personalized Educational Recommendations in Secondary Education through Deep Q-Learning Optimization

Team Name : Pathfinders

Team Members : Md Fahim Muntasir | Mohammad Faisal Chowdhury | Himadri Bhowmick

Supervisor: Most. Fatematuz Zohora

Bangladesh Army International University of Science & Technology (BAIUST)

Team No. : 01
POSTER No: CSE-01
Dept. : CSE

INTRODUCTION

E-learning systems revolutionized education, giving secondary-level students the opportunity to learn from anywhere in the world. But, the quantity of online courses and activities can leave students overwhelmed, making it difficult to choose what works. The proposed paper presents a Deep Q-Learning based framework to improve the secondary level e-learning process by customized learning path and content recommendations based on Markov Decision Process (MDP) techniques.

The system predicts learners' needs based on past interactions, dynamically adjusting recommendations such as lessons, quizzes, and exercises to maximize engagement and minimize frustration. The framework offers a promising solution to enhance personalized e- learning experiences for secondary-level students.

METHODOLOGY

Deep Q-Learning Framework

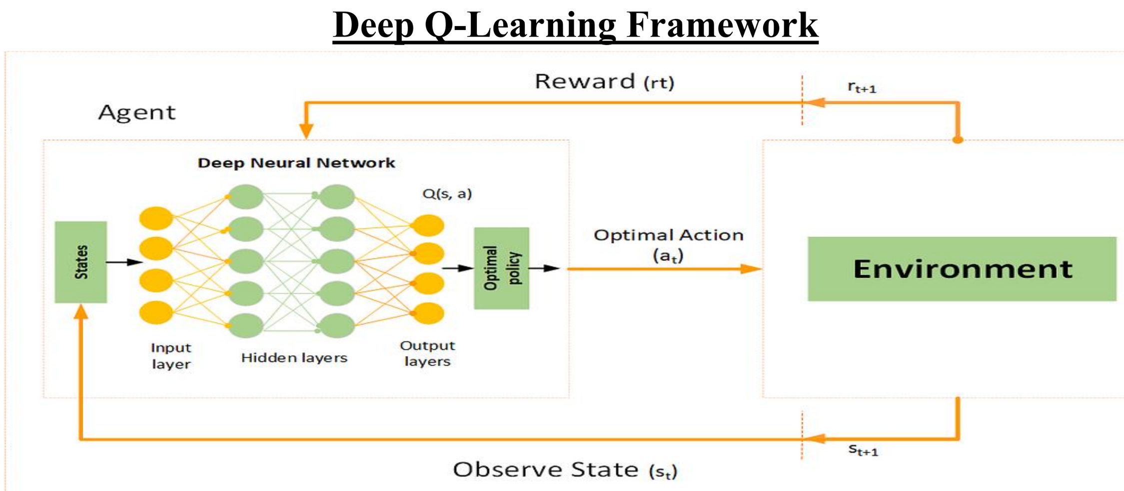

Figure 1: Deep Q-Learning structure

Deep Q-Learning introduces a second neural network, called the target network, [2] which is used to calculate the target Q-values. This target network is updated less frequently than the main network to prevent rapid oscillations in learning.

The rule for Deep Q-Learning is based on the Bellman equation:

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left(r + \gamma \max_{a'} Q(s',a';\theta^-) - Q(s,a;\theta)\right)$$

PROCESS WORKFLOW

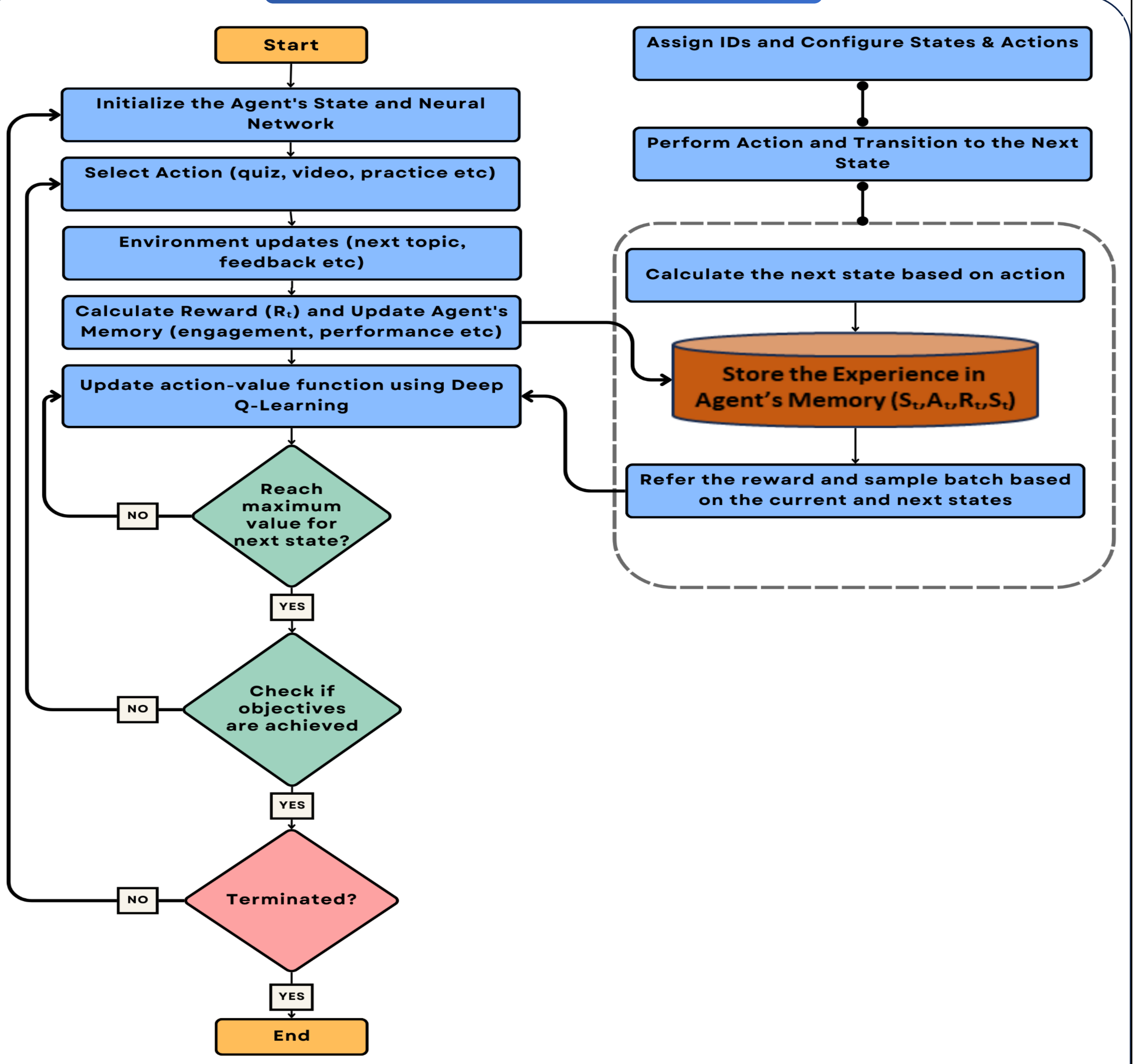

Figure 2: Flowchart of the proposed Deep Q-Learning algorithm.

- This flowchart shows how an e-learning system uses Deep Q-Learning to personalize learning by selecting actions, updating based on feedback, and improving over time.

STATES DIAGRAM &REWARD TABLE

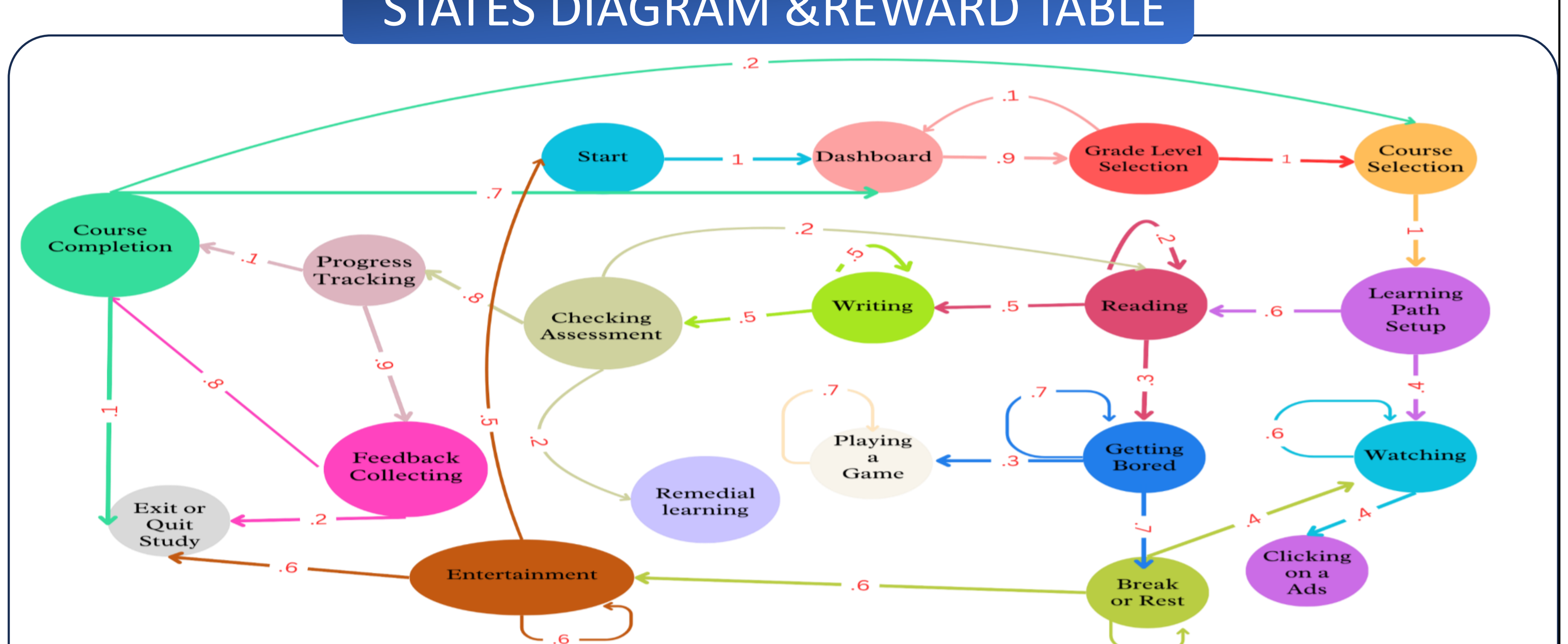

Figure 3: State diagram for adaptive E-learning.

- **State Diagram**: This diagram visually represents the states that a student goes through while learning. It shows how students move from one state to another,

Action	Action Reward
Stay: Study More	+5
Review Prerequisite Topics	+3
Explore Additional Content	+4
Assign Quizzes or Mini-Assignments	+6
Prepare for Tests	+7
Focus on High-Level Challenges	+8
Break Down to Lower-Level Concepts	+2
Fun Learning Activities	+5
Suggest Rest or Breaks	0
Course Completion and Rewards	+10
Encourage Hands-On Learning	+8
Suggest Offline Exploration	+1

Table 1: List of Reward for each action.

- **Reward Table**: This table outlines the specific rewards that students can earn based on their actions within the learning platform.

FRAMEWORK

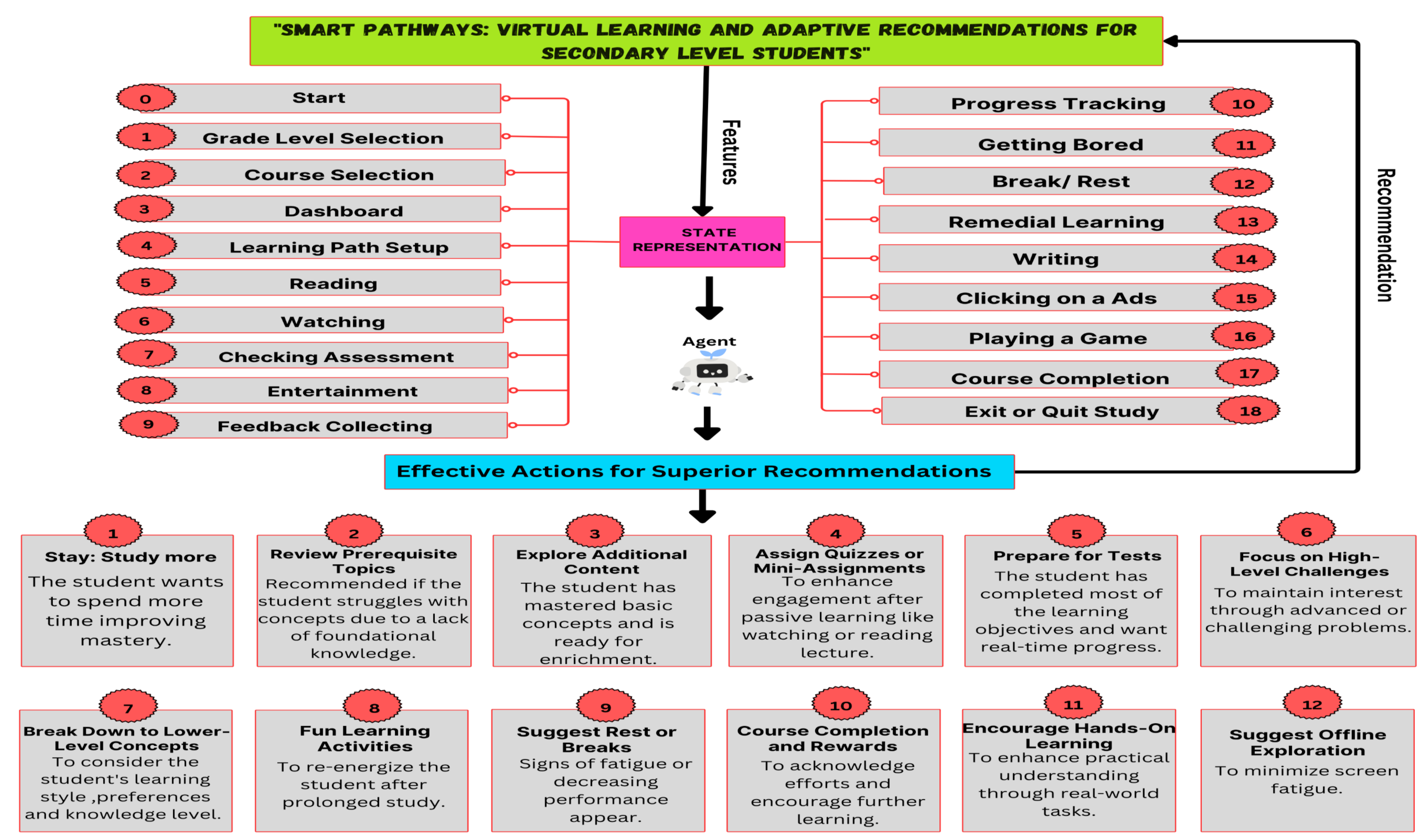

Figure 4: Framework of E-Learning and Adaptive Recommendations process.

- Representation of a virtual learning platform that offers personalized learning paths and recommendations for secondary students.

RESULTS AND DISCUSSION

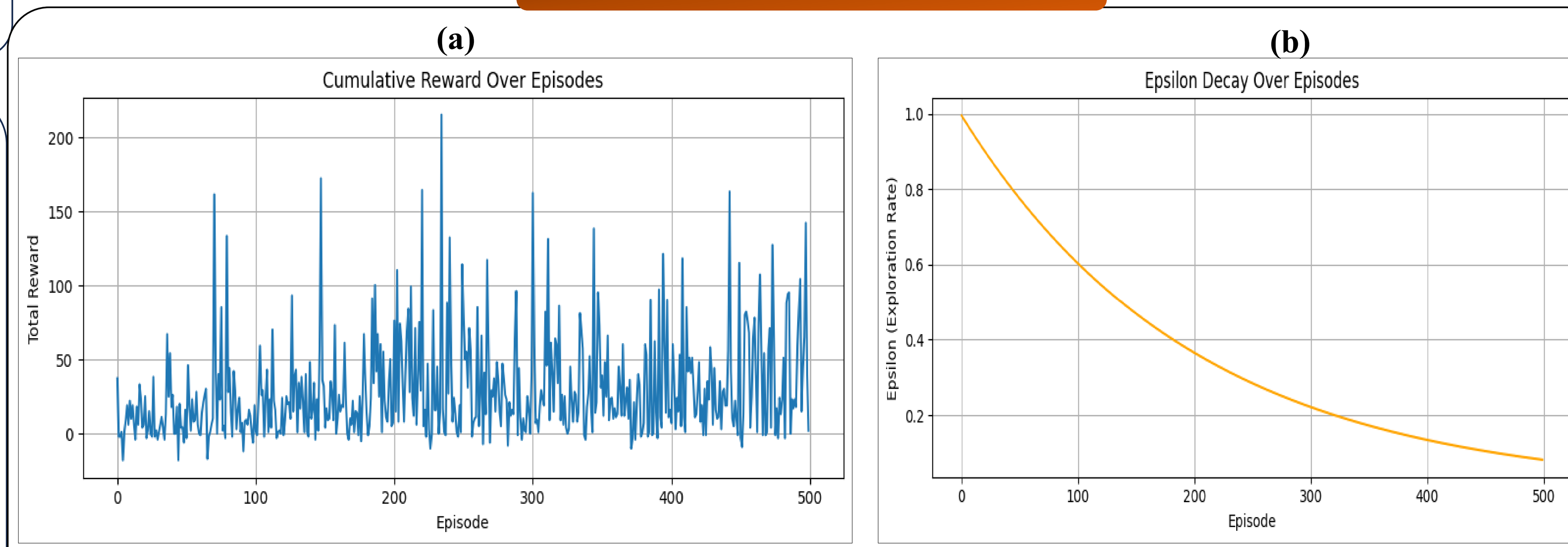

Figure 5: (a) Cumulative reward over 500 episodes how the agent's performance improves through training. (b) The Epsilon Decay curve over 500 episodes.

- **Epsilon (ε)** controls how much the agent explores (random actions) vs. exploits (learned best actions).
- High **ε** = more random = early training . Low **ε** = more confident = stable performance.

- **Best Action per State:**

State	Best Action	State	Best Action
Grade Level Selection	Course Completion and Rewards	Progress Tracking	Explore Additional Content
Course Selection	Review Prerequisite Topics	Getting Bored	Suggest Rest or Breaks
Dashboard	Prepare for Tests	Break/Rest	Prepare for Tests
Learning Path Setup	Course Completion and Rewards	Remedial Learning	Break Down to Lower-Level Concepts
Reading	Stay: Study More	Writing	Encourage Hands-On Learning
Watching	Review Prerequisite Topics	Clicking on Ads	Fun Learning Activities
Checking Assessment	Fun Learning Activities	Playing a Game	Review Prerequisite Topics
Entertainment	Review Prerequisite Topics	Course Completion	Course Completion and Rewards
Feedback Collecting	Stay: Study More		

Table 2 : The best learning action the agent recommends for each student state based on 500 episodes training.

- **Action Frequency:**

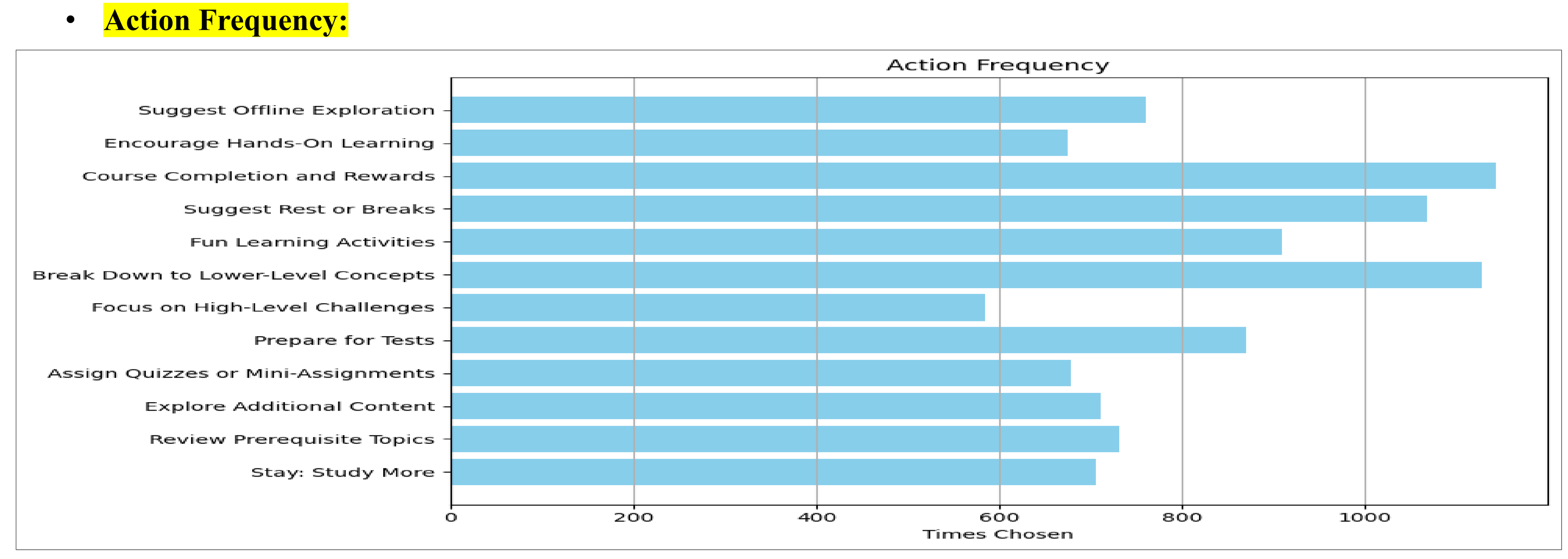

Figure 6: The action frequency reveals after 500 episodes which learning strategies were most recommended by the agent.

- After 500 episodes, the AI agent learned to give smart, personalized learning suggestions.
- The reward increased over time.[fig: 5(a)]
- The epsilon decay curve showed that the model became more confident .[fig: 5(b)]
- The most used actions matched the right student needs .[fig: 6]
- Proving that Deep Q-Learning can build an effective personalized e-learning system.

CONCLUSION

The proposed Deep Q-Learning-based framework addresses the challenges of secondary education in Bangladesh by leveraging personalized learning paths and adaptive recommendations. By incorporating Markov Decision Processes, the system dynamically adjusts content to maximize engagement and minimize frustration. It aims to overcome issues like teacher shortages, inadequate infrastructure, and **reliance on rote learning**. The anticipated outcomes include enhanced accessibility to digital resources, **reduced dropout rates**, and a significant shift towards personalized and **interactive learning experiences**. This innovative approach has the potential to revolutionize education for underprivileged students in Bangladesh.

REFERENCES

[1] S. Amin, M. I. Uddin, A. A. Alarood, W. K. Mashwani, A. Alzahrani and A. O. Alzahrani,2023,"Smart E-Learning Framework for Personalized Adaptive Learning and Sequential Path Recommendations Using Reinforcement Learning," in IEEE Access, vol. 11, pp. 89769-89790, https://doi.org/10.1109/ACCESS.2023.3305584 .

[2] https://medium.com/@samina.amin/deep-q-learning-dqn-71c109586bae