Journal of Information & Optimization Sciences
ISSN 0252-2667 (Print), ISSN 2169-0103 (Online)
Vol. 46 (2025), No. 6, pp. 1793–1801
DOI : 10.47974/JIOS-2008

The scalable cloud-based reinforcement learning for multimedia data in cognitive Neuroscience for secure healthcare analysis

Venkateswara Rao Bolla §
Department of Computer Science Engineering (AI & ML)
St. Martin's Engineering College
Dhulapally
Secunderabad 500100
Telangana
India

B. Vikas †
Department of Computer Science and Engineering
Sreenidhi University
Ghatkesar
Hyderabad 501301
Telangana
India

Sirisha Potluri *
Department of Computer Science and Engineering
Koneru Lakshmaiah Education Foundation
Bowrampet
Hyderabad 500043
Telangana
India

§ *ORCID-ID:* 0000-0002-8812-0909
† *ORCID-ID:* 0000-0002-4040-1189
* *ORCID-ID:* 0000-0001-9106-9780

§ *E-mail:* venki.bolla@gmail.com
† *E-mail:* vikasboddu30@gmail.com
* *E-mail:* sirisha.vegunta@gmail.com (Corresponding Author)

Yerragudipadu Subbarayudu [‡]
Department of Computer Science and Engineering
Koneru Lakshmaiah Education Foundation
Bowrampet
Hyderabad 500043
Telangana
India

G. Sucharitha [@]
Department of Computer Science and Engineering
Anurag University
Venkatapur Village
Hyderabad 500088
Telangana
India

Nirmalajyothi Narisetty [#]
Department of Computer Science and Engineering
Koneru Lakshmaiah Education Foundation
Bowrampet
Hyderabad 500043
Telangana
India

Abstract

Recently, the field of neuroscience and the complexity of brain research data have increased due to advancements in imaging technologies, electrophysiological recordings, and genetic sequencing. Managing and organizing this vast amount of data is a big challenge. Our research explores the integration or participation of cloud-based multimedia data systems in cognitive neuroscience and brain research, emphasizing their role in data storage, security, retrieval, encryption, and analysis. Technology addresses these challenges, providing data storage and more efficient data analysis methods. As neuroscience continues to evolve, generating increasingly complex datasets, the role of multimedia data systems becomes crucial in unlocking brain functions and understanding neurological disorders. Additionally, cloud-based multimedia data systems offer scalable and cost-effective solutions for storing and processing large neuroscience datasets. Reinforcement learning (RL) approaches are gradually being explored for healthcare applications, especially neuroscience. The proposed RL algorithm is devised to learn and acquire optimal actions

[‡] *ORCID-ID:* **0000-0003-0349-9831**
[@] *ORCID-ID:* **0000-0001-7861-2451**
[#] *ORCID-ID:* **0000-0002-4810-9676**

[‡] *E-mail:* **subbu.jntua@gmail.com**
[@] *E-mail:* **sucharithasu@gmail.com**
[#] *E-mail:* **nirmala.narisetty@klh.edu.in**

via a trial-and-error methodology steered by rewards or penalties. The proposed RL model transforms cognitive and neural procedures into formal scientific structures. This facilitates realizing and modeling how the brain can learn from events and generate decisions. Results and outcomes demonstrate that the proposed model outperforms the existing state-of-the-art models.

Subject Classification: *68U10, 68M20, 92C55.*

Keywords: *Cognitive neuroscience, Data analysis, Data validation, Electrophysiology, Image processing, Multimedia data, Neuroimaging, Reinforcement learning.*

1. Introduction

Imagine building blocks that can be combined to make bigger things [1]. This model is like using building blocks to represent parts of the brain. It can show how different parts of the brain work together [2]. For example, scientists can see how the part of your brain that sees things works with the part that helps you understand what you see [3, 4]. Extend relational databases to handle complex data structures like brain images and electrophysiological recordings. Centralized repositories that integrate data from multiple sources allow researchers to analyze data across different studies. Like a family tree with parents and children. Information is organized in a tree-like structure with levels [5, 6]. This model can be used to represent brain regions and their subdivisions. These are flexible models that don't follow strict rules like relational databases [7]. They are good for handling large amounts of unstructured or semi-structured data, like text from research papers or images from brain scans [8]. Common NoSQL models include Document-oriented (like MongoDB), Key-value (like Redis), and Graph (like Neo4j). Object-oriented models can be used to represent complex brain structures and their functions. Hierarchical models are useful for organizing brain regions and their relationships [9, 10]. NoSQL models are becoming increasingly popular for handling large and complex brain datasets, especially in areas like connectomics and natural language processing of brain research.

2. Materials and Methods

Electronic lab notebooks (ELNs) are electronic platforms specifically designed for scientific research to record protocols, data, and analysis results in a centralized and searchable way. Open Neuro is a public repository for sharing neuroimaging data, promoting data sharing and collaboration among researchers. XNAT is an open-source neuroinformatics platform for managing and sharing neuroimaging data. These existing models and systems provide a foundation for data storage, organization, and sharing in cognitive neuroscience [11]. However, there's a continuous effort to improve data integration and analysis capabilities. Imagine scientists are detectives trying to solve the mystery of the brain. They use special tools to collect clues [12]. These clues are like puzzle pieces, and they need a special place to be them in an organized manner. Brain databases are like super-organized filing cabinets for all the information scientists collect about the brain. They store multimedia data like 1) Brain scans, pictures of the brain, 2) Experiment results, what happened when scientists did tests, and 3) Patient information, details about people who help with the research. NoSQL Databases are like big boxes where you can put anything, even if it's not perfectly organized. They're good for storing different types of information, like pictures and videos. Specialized Brain Databases are made just for brain research. They have special tools to help scientists analyze brain data. The Open Access Series of Imaging Studies (OASIS) database has brain scans of healthy people. The Human Connectome Project (HCP) [13, 14] database studies how different parts of the brain are connected.

3. Model

Combining two types of data and working them together isn't an easy thing in the neuroscience field, where data from genetics, brain imaging, and all other remaining sources must be combined, and it is too complex to understand issues like brain functions and brain disorders. Hence, big data systems provide interoperability, supporting data access, and analysis. The Asynchronous Advantage Actor-Critic (A3C) is an advanced reinforcement learning (RL) algorithm that combines both value-based and policy-based methods. In healthcare and cognitive neuroscience, A3C can be applied to various tasks such as optimizing treatment plans, real-time patient monitoring, and personalized healthcare strategies. Table 1 describes the proposed algorithm can teach you to make real-time decisions based on data streaming from brain activity sensors to improve patient outcomes by adapting dynamic decision-making. Multi-agent reinforcement Learning (MARL) in the context of scalable cloud-based systems for healthcare involves a series of coordinated steps where multiple agents operate within a shared environment to achieve specific goals, such as optimizing patient care, resource allocation, or emergency response [15].

Table 1

Algorithms of the proposed model

A3C

```
START
  |
  |--> Import input data
  |   - add libraries threading
  |   - numpy as np
  |   - tensorflow as tf
  |   - gym
  |
  |--> Define Hyperparameters
  |   - NUM_WORKERS = 4
  |   - MAX_EPISODES = 1000
  |   - GAMMA = 0.99
  |   - LR = 0.001
  |
  |--> Define Functions
  |   |--> build_actor_critic
  |   |   - Define input shape and action space
  |   |   - Create common layers
  |   |   - Create actor and critic networks
  |   |   - Return combined model
  |   |
  |   |--> Worker Class (Asynchronous Agents)
  |   |   |--> __init__ method
  |   |   |   - Initialize worker ID, global model, optimizer, environment
  |   |   |   - Build local model
  |   |   |
  |   |   |--> run method
  |   |   |   |--> FOR each episode (0 to MAX_EPISODES)
  |   |   |   |   |--> Reset environment
  |   |   |   |   |--> WHILE not done
  |   |   |   |   |   |--> Select action
  |   |   |   |   |   |--> Perform action in environment
  |   |   |   |   |   |--> Compute advantage and update local model
  |   |   |   |   |   |--> Update state
  |   |   |   |   |   |--> Check if done
  |   |   |   |   |--> Update global model
  |   |   |
  |   |   |--> select_action
  |   |   |   - Get action probabilities and value
  |   |   |   - Choose action based on probabilities
  |   |   |   - Return action and value
  |   |   |
  |   |   |--> train_step
  |   |   |   - Compute target and advantage
  |   |   |   - Compute loss (actor + critical loss)
  |   |   |   - Update local model weights
  |   |   |
  |   |   |--> update_global_model
  |   |       - Synchronize local model with global model
  |
  |--> Main Function
  |   |--> Initialize environment and global models
  |   |--> Create optimizer
  |   |--> Spawn and start worker threads
  |   |--> Wait for all workers to complete
  |
  |--> END
```

MARL

```
START
|
|--> Import `input data
|
|--> Define constants: NUM_AGENTS = 5, MAX_EPISODES = 100
|
|--> Define functions:
|     - initialize_cloud_environment
|     - initialize_agent_policy(agent_id)
|     - observe_environment
|     - select_action (policy, state)
|     - step_environment(action)
|     - store_experience (state, action, reward, next_state)
|     - update_local_policy(agent_id)
|     - share_information_with_other_agents(agent_id)
|     - update_global_policy
|     - evaluate_system_performance
|     - check_performance_threshold_met
|
|--> MAIN FUNCTION
|   |
|   |--> Initialize cloud environment
|   |--> Initialize each agent's local policy
|   |
|   |--> FOR each episode (1 to MAX_EPISODES):
|   |   |
|   |   |--> FOR each agent (1 to NUM_AGENTS):
|   |   |   |
|   |   |   |--> Observe the environment
|   |   |   |--> WHILE not terminal state:
|   |   |   |   |
|   |   |   |   |--> Select action based on state and policy
|   |   |   |   |--> Step into environment: get next state and reward
|   |   |   |   |--> Store experience
|   |   |   |   |--> Update local policy
|   |   |   |   |--> IF communication allowed, share information
|   |   |   |   |--> Update state
|   |   |   |   |--> IF global update required, update global policy
|   |   |   |   |--> Check if terminal state is reached randomly
|   |   |
|   |   |--> Evaluate system performance
|   |   |--> IF performance threshold met, break
|   |
|   |--> Print "Training completed"
|
END
```

Result Analysis

Table 2 evaluates the performance of four reinforcement learning methods—Independent Q-Learning (IQL), Conservative Q-Learning (CQL), A3C, and MARL across multiple metrics like accuracy, precision, recall, and F1 score. The task involves scalable cloud-based reinforcement learning for multimedia data in cognitive neuroscience for secure healthcare analysis, with the evaluation being done for different numbers of topics: 50, 100, 150, and 200. Among them, the most accurate is MARL at 50 topics with an accuracy rate of 98.71 % which has a precision of 0.98, recall of 0.93, and F1 score of 0.93(due to hard reference) hence it is highly reliable in this case A3C also achieves high performance with 96.64% accuracy, but the recall is reduced with a slightly lower value of 0.87, resulting in an F1 score of 0.83. With an accuracy of only about 67%, both IQL and CQL perform significantly worse (F1 scores around 0.69 and 0.73), indicating that they are less capable of addressing the complexity of this task with 50 topics from free text data.

Table 2

Performance evaluation of reinforcement learning technique

Method	Accuracy (%)	Precision	Recall	F1 Score	Topics
IQL	67.52	0.66	0.73	0.69	50
CQL	66.95	0.68	0.75	0.73	50
A3C	96.64	0.92	0.87	0.83	50
MARL	98.71	0.98	0.93	0.93	50
IQL	56.20	0.66	0.69	0.68	100
CQL	58.98	0.68	0.71	0.69	100
A3C	89.44	0.92	0.89	0.89	100
MARL	94.46	0.92	0.93	0.94	100
IQL	62.76	0.72	0.77	0.77	150
CQL	59.32	0.72	0.69	0.69	150
A3C	91.22	0.94	0.92	0.89	150
MARL	94.77	0.95	0.94	0.96	150
IQL	60.66	0.72	0.77	0.78	200
CQL	63.44	0.73	0.79	0.74	200
A3C	91.88	0.88	0.89	0.89	200
MARL	93.44	0.92	0.97	0.87	200

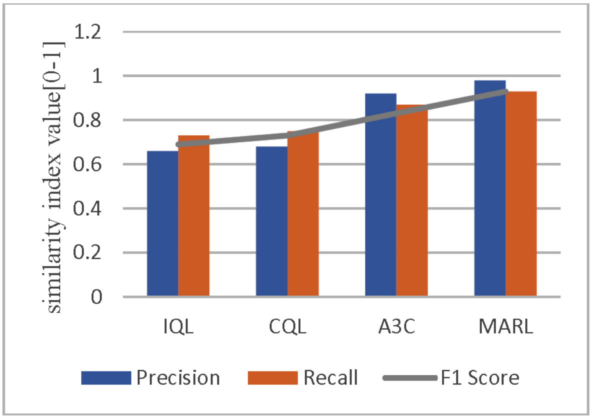

Figure 1

Comparison of results- Performance evaluation

Figure 1 compares four baseline approaches — Independent Q-Learning (IQL), Conservative Q-Learning (CQL), Asynchronous Advantage actor-critic (A3C), and Multi-Agent Reinforcement Learning (MARL) performance on three main evaluation metrics — Precision, Recall, and F1 Score.

4. Conclusion

This model can also be broadly expanded to broader healthcare domains, such as diagnosis of mental health conditions, real-time brain-computer interfaces, or personalized cognition therapy as the intersection between cognitive neuroscience and AI continues to grow. More importantly, quantum computing could take learning processes light years ahead of current capabilities by many orders of magnitude and lead us to real-time, secure, and efficient healthcare solutions.

References

[1] D. Goyal, A. Kumar, and D. S. Jat, "Special issue on advancements in intelligent systems for information optimization in cyber security: Challenges and innovations (Part-B)," *Journal of Discrete Mathematical Sciences and Cryptography*, vol. 28, no. 5-B, pp. i–viii (2025).

[2] P. R. Kumar, T. K. Mohammad, A. P. Kumar, R. Kassym, A. S. Togelenova, and A. Tlenshieva, "Synthesizing multi-modal imaging for

enhanced brain mapping in neurology: A state-of-the-art review," in Proc. 5th Int. Conf. Communications, Information, Electronic and Energy Systems (CIEES), pp. 1–6 (2025).

[3] M. Hasani and M. Ghods, "Investigating fuzzy topological indices of linear and multi-cyclic Naphtalene," *Journal of Interdisciplinary Mathematics*, vol. 28, no. 5, pp. 1779–1793 (2025).

[4] P. R. Kumar, B. Shilpa, and R. K. Jha, "Brain disorders: Impact of mild SARS-CoV-2 may shrink several parts of the brain," *Neuroscience & Biobehavioral Reviews*, vol. 149, Art. no. 105150 (2023).

[5] G. S. Aujla, A. Jindal, D. B. Rawat, and C. Jiang, "Deep neuro-fuzzy analytics for intelligent big data processing in smart ecosystems," *Neural Computing and Applications*, vol. 35, no. 33, pp. 23667–23669 (2023).

[6] D. L. Barabási, G. Bianconi, E. Bullmore, M. Burgess, S. Chung, T. Eliassi-Rad, … and G. Buzsáki, "Neuroscience needs network science," *Journal of Neuroscience*, vol. 43, no. 34, pp. 5989–5995 (2023).

[7] P. R. Kumar, R. K. Jha, and P. A. Kumar, "Brain hyperintensities: automatic segmentation of white matter hyperintensities in clinical brain MRI images using improved deep neural network," *The Journal of Supercomputing*, vol. 80, no. 11, pp. 15545–15581 (2024).

[8] N. Racshitha and R. Manimaran, "Solving stochastic delay differential equation by using Runge-Kutta method and method of lines," *Journal of Interdisciplinary Mathematics*, vol. 28, no. 5, pp. 1871–1879 (2025).

[9] P. Chinnasamy, A. Albakri, M. Khan, A. A. Raja, A. Kiran, and J. C. Babu, "Smart contract-enabled secure sharing of health data for a mobile cloud-based e-health system," *Applied Sciences*, vol. 13, no. 6, Art. no. 3970 (2023).

[10] J.-M. Chen, "Multi-vendor and multi-buyer collaborative planning, forecasting and replenishment model," *Journal of Statistics and Management Systems*, vol. 28, no. 6, pp. 1023–1036 (2025).

[11] P. R. Kumar, B. Shilpa, R. K. Jha, and V. S. Chellibouina, "Spatial attention U-Net model with Harris hawks optimization for retinal blood vessel and optic disc segmentation in fundus images," *International Ophthalmology*, vol. 44, Art. no. 359, pp. 1–13 (2024).

[12] A. K. Saini, M. L. Saini, D. K. Srivastava, S. Singh, P. Vats, and T. K. Tak, "Secure communication framework using lattice-based encryp-

tion and image steganography," *Journal of Discrete Mathematical Sciences and Cryptography,* vol. 28, no. 5-B, pp. 1855–1864 (2025).

[13] G. Lăzăroiu, M. Bogdan, M. Geamănu, L. Hurloiu, L. Luminița, and R. Ștefănescu, "Artificial intelligence algorithms and cloud computing technologies in blockchain-based fintech management," *Oeconomia Copernicana*, vol. 14, no. 3, pp. 707–730 (2023).

[14] P. R. Kumar, B. Shilpa, and R. K. Jha, "BrainTract: Segmentation of white matter fiber tractography and analysis of structural connectivity using hybrid convolutional neural network," *Neuroscience,* vol. 580, pp. 218–230 (2025).

[15] P. R. Kumar, R. K. Jha, P. A. Kumar, and B. D. Raju, "Improved neurological diagnoses and treatment strategies via automated human brain tissue segmentation from clinical magnetic resonance imaging," *Intelligent Medicine*, vol. 4, no. 3, pp. 161–169 (2024).

Received December, 2024