Cognitive-Aware Deep Reinforcement Learning Framework for Intelligent Health Monitoring Using IoT and Digital Twin Integration

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ABSTRACT: In recent years, the convergence of Artificial Intelligence (AI), the Internet of Things (IoT), and Digital Twin (DT) technologies has opened new frontiers in intelligent healthcare systems. However, current deep reinforcement learning (DRL) models are primarily focused on physiological monitoring or resource management, overlooking the cognitive and behavioral dimensions that play a critical role in human health. This research proposes a Cognitive-Aware Deep Reinforcement Learning Framework that integrates IoT-based physiological sensors, behavioral data, and digital twin simulations to predict and manage cognitive states such as forgetfulness, distractibility, and false triggering in real time. The framework leverages a digital twin environment to mirror the user's cognitive and physical conditions, enabling adaptive learning and proactive decision-making. Furthermore, an edge–cloud collaborative architecture is designed to optimize latency, computation, and energy efficiency for continuous health monitoring. Privacy-preserving data fusion techniques are incorporated to ensure secure and reliable integration of multimodal data from distributed IoT sources. The DRL model is enhanced with explainable AI (XAI) mechanisms to provide transparent decision insights, making it suitable for clinical interpretation and personalized care. Experimental evaluations using real-world and simulated datasets demonstrate improvements in prediction accuracy, energy efficiency, and system adaptability compared to traditional machine learning approaches. The proposed framework establishes a new paradigm for intelligent healthcare by unifying cognitive modeling, deep reinforcement learning, and digital twin technologies—laying the foundation for proactive, personalized, and trustworthy cognitive health management systems.

Keywords — ***Cognitive-Aware Healthcare, Deep Reinforcement Learning (DRL), Internet of Things (IoT), Digital Twin (DT), Edge–Cloud Computing, Cyber-Physical Systems (CPS), Cognitive State Prediction, Explainable Artificial Intelligence (XAI), Multimodal Data Fusion, Real-Time Monitoring, Resource Optimization, Privacy-Preserving AI.***

I. INTRODUCTION

The rapid advancement of Artificial Intelligence (AI), the Internet of Things (IoT), and Digital Twin (DT) technologies has revolutionized the way healthcare systems monitor, analyze, and manage patient health in real time. With the increasing prevalence of chronic diseases, mental health challenges, and cognitive impairments, there is a growing need for intelligent systems capable of providing continuous, adaptive, and personalized healthcare solutions. Traditional healthcare monitoring systems are largely reactive and focus primarily on physiological signals such as heart rate, temperature, and blood pressure, neglecting crucial cognitive aspects like forgetfulness, distractibility, and false triggering that significantly influence overall well-being. Recent studies have demonstrated the potential of Deep Reinforcement Learning (DRL) as a self-learning approach capable of optimizing complex decision-making processes in uncertain and dynamic environments such as healthcare IoT networks. However, existing DRL-based health systems are often limited to specific tasks like activity recognition or resource allocation and fail to integrate cognitive data, multi-sensor fusion, and dynamic feedback through digital twins. The concept of a Digital Twin a virtual representation of a physical entity offers an unprecedented opportunity to simulate, predict, and optimize patient conditions before real-world execution, thereby improving reliability and safety. By coupling DRL with digital twin technology, healthcare systems can continuously learn from both simulated and real-world feedback, achieving context-awareness and proactive health management. Furthermore, deploying such intelligent frameworks in edge–cloud collaborative environments enhances scalability and responsiveness while reducing latency in data transmission, which is essential for real-time patient monitoring. Despite these advancements, challenges such as data heterogeneity, lack of explainability, privacy concerns, and the absence of unified frameworks for cognitive-aware decision-making remain unresolved. To address these issues, this research proposes a Cognitive-Aware Deep Reinforcement Learning Framework that integrates IoT-based health data, behavioral analysis, and digital twin modeling to enable adaptive cognitive and physiological monitoring. The framework aims to achieve efficient learning at the edge, ensure privacy-preserving multimodal data fusion, and provide interpretable decision-making for clinical and personal health applications. This study contributes to the next generation of intelligent healthcare systems that move beyond traditional physiological monitoring towards holistic, explainable, and proactive cognitive health management, bridging the gap between human cognition and machine intelligence.

II. LITERATURE REVIEW

Abdellatif et al. (2023) [1] provided a comprehensive review of reinforcement learning (RL) applications in intelligent healthcare systems, identifying major challenges such as scalability, real-time learning, and the need for distributed computing architectures. The study emphasized that integrating IoT and RL can significantly improve remote monitoring and decision-making for patients. Similarly, Wang et al. (2025) [2] proposed a deep-reinforcement-learning-driven patient state analysis framework that optimized resource management in near-field IoE healthcare networks. Their work demonstrated that twin delayed deep deterministic policy gradient (TD3) algorithms could effectively handle dynamic healthcare environments. However, these studies primarily focus on physiological state estimation and overlook the cognitive aspects of healthcare, such as forgetfulness and attention, which are vital for holistic patient assessment.

Ye et al. (2024) [4] introduced a Deep Reinforcement Learning (DRL)–based activity-aware health monitoring system capable of real-time tracking and energy-efficient operations. Their work showed that DRL can dynamically balance system cost and accuracy. Xu et al. (2025) [5] further extended this by combining DDPG algorithms with graph-based schemes for efficient resource management in digital twin-assisted biomedical systems**,** emphasizing optimization and reliability in healthcare cyber-physical systems. These models, though effective in resource allocation, did not incorporate cognitive or behavioral factors into decision-making. Thus, while DRL has shown promising results in enhancing computational and resource efficiency, it lacks integration with cognitive modeling for complete patient monitoring.

Digital Twin (DT) technology has emerged as a transformative concept in healthcare. Roopa and Venugopal (2025) [16] analyzed DT-based cyber-physical healthcare systems**,** outlining their architecture, requirements, and operational benefits for precision medicine and real-time diagnostics. Likewise, Tran et al. (2025) [8] and Sheraz et al. (2024) [12] explored AI-enabled digital twin networks for 6G communication environments, emphasizing connectivity, real-time synchronization, and predictive analytics. These studies highlight DT's potential for simulating and optimizing health conditions virtually before real-world interventions. However, they primarily focus on system-level architecture and networking rather than integrating DRL for patient-specific cognitive or physiological adaptation**.** This creates an opportunity to embed reinforcement learning within digital twin environments for adaptive healthcare intelligence.

Several studies such as Ullah et al. (2025) [14] and Sharif and Seker (2024) [10] addressed resource management and optimization using DRL in mobile edge computing and smart environments. Ullah et al. surveyed DRL applications in MEC-enhanced networks**,** showing that mobile edge computing can enable low-latency decision-making. Sharif and Seker focused on smart EV charging through context-aware DRL, improving energy utilization and cost-efficiency. In the healthcare context, similar optimization principles can enhance energy efficiency and response time in IoT-based health systems. Yet, none of these works explored cognitive-aware resource management**,** where system resources are dynamically allocated based on a user's cognitive state or workload.

Khan et al. (2022) [18] conducted a systematic review on AI and IoT integration during the COVID-19 pandemic**,** emphasizing data-driven diagnostic and remote patient monitoring applications. Their study revealed the power of AI-IoT fusion in managing large-scale health crises. Similarly, Abdellatif et al. (2023) [1] and Awaisi et al. (2024) [20] highlighted opportunities and challenges in Industrial and Medical AIoT systems**,** particularly focusing on interoperability, security, and latency issues. These findings confirm that while AI-IoT frameworks are effective for healthcare data acquisition, they require more advanced learning mechanisms such as DRL for adaptive cognitive analysis and prediction.

Ma et al. (2024) [7] explored deep reinforcement learning for cybersecurity**,** proving its potential in dynamic threat detection and response. Similarly, the studies by Sheraz et al. (2024) [12] and Tran et al. (2025) [8] emphasized security and trust management in digital twin networks. However, explainability and ethical transparency remain underexplored in most DRL-based healthcare systems. The lack of interpretability limits clinical trust and the acceptance of AI-driven cognitive decision systems. Future healthcare models must thus incorporate Explainable AI (XAI) within DRL frameworks to ensure safe and comprehensible decision-making.

III. METHODOLOGY

3.1 System Design

The proposed methodology aims to design and develop a Cognitive-Aware Deep Reinforcement Learning (DRL) Framework that integrates IoT-based health monitoring systems with Digital Twin (DT) technology for intelligent, adaptive, and personalized healthcare management. This framework focuses on both physiological and cognitive parameters**,** thereby bridging the gap between traditional health monitoring systems that track only physical signals and modern AI-driven systems that also assess cognitive well-being. The methodology follows a multi-layered, modular approach consisting of data acquisition through IoT sensors, data preprocessing and fusion, cognitive state estimation using machine learning models, reinforcement learning-based decision optimization, and simulation through digital twin environments for validation and feedback. In the first phase, IoT-enabled sensors are deployed to collect real-time physiological data such as heart rate, EEG signals, temperature, and blood oxygen levels, along with behavioral and cognitive indicators such as attention span, forgetfulness, and false triggering. This multimodal data is transmitted securely to a cloud–edge computing infrastructure, enabling distributed processing and minimizing latency. In the second phase, data preprocessing is carried out, which involves noise removal, normalization, and feature extraction to ensure that the input to the cognitive model is consistent and reliable.

Next, the system employs a Deep Reinforcement Learning model that continuously learns from user-specific patterns and environmental changes. The DRL agent uses historical and real-time data to make optimal health-related decisions, such as predicting cognitive decline, detecting early signs of mental fatigue, or recommending interventions. The reward function within the reinforcement learning model is carefully designed to balance multiple objectives maximizing accuracy, minimizing false alarms, and ensuring user comfort and energy efficiency in IoT devices. A core component of this methodology is the Digital Twin**,** which acts as a virtual replica of the patient or the monitored system. The DT simulates various health scenarios, allowing the DRL model to test and validate its decisions before real-world implementation. This digital feedback loop enhances safety and reliability, enabling proactive health management rather than reactive care. The twin continuously synchronizes with real-world data to maintain dynamic alignment and improve predictive accuracy. Finally, the framework integrates all modules into a unified cognitive-aware monitoring system**.** The integration of IoT, AI, and Digital Twin technologies enables real-time analysis, adaptive decision-making, and intelligent feedback generation. The system's performance is evaluated using key metrics such as prediction accuracy, response time, energy efficiency, and user satisfaction. In essence, the proposed methodology provides a holistic and intelligent health monitoring ecosystem that not only observes physiological signals but also interprets cognitive states, predicts potential anomalies, and recommends personalized interventions. This methodological design thus contributes to the development of next-generation healthcare systems capable of self-learning, context-awareness, and real-time adaptability addressing the growing need for proactive, personalized, and cognitive-driven health management.

3.2 Workflow of the project

The workflow of the proposed Cognitive-Aware Deep Reinforcement Learning Framework integrates data collection, analysis, learning, and decision-making into a continuous and adaptive health monitoring loop. The framework ensures seamless interaction between IoT devices, machine learning models, and Digital Twin simulations, enabling real-time, personalized, and cognitive-aware healthcare management.

A. Data Acquisition via IoT Sensors

The process begins with the deployment of IoT-based biomedical and cognitive sensors that collect physiological and behavioral data from users.

- Physiological signals include heart rate, EEG, temperature, blood pressure, and oxygen saturation.
- Cognitive indicators include forgetfulness, distractibility, attention span, and emotional state. These data streams are transmitted through a secure edge-cloud communication channel using protocols such as MQTT or CoAP. The IoT layer ensures continuous, low-latency monitoring and forms the foundation of the entire framework.
- **Data Preprocessing and Feature Extraction**

  The collected raw data are often noisy, incomplete, or redundant. Hence, a preprocessing module is implemented to perform:

  - Noise reduction (using filters such as Butterworth or wavelet denoising),
  - Missing value imputation (via mean/mode or kNN),
  - Normalization and scaling (using Min-Max or Z-score methods). Feature extraction techniques such as Principal Component Analysis (PCA) and Statistical Feature Mapping are applied to derive meaningful parameters that describe both physical and cognitive states. This ensures data quality before feeding into learning algorithms.

B. Cognitive State Analysis and Classification

The processed data are analyzed to classify the user's cognitive condition (e.g., Mild, Moderate, High cognitive decline or fatigue).

Machine learning and deep learning models (e.g., Random Forest, Decision Tree, CNN-LSTM) are used to detect patterns related to cognitive performance.

This stage acts as a diagnostic layer, generating insights that support the reinforcement learning model in later stages.

C. Deep Reinforcement Learning-Based Decision Optimization

This is the core of the proposed system, where a Deep Reinforcement Learning (DRL) agent is trained to make dynamic and intelligent decisions.

- The agent interacts with the environment (real-time health data + Digital Twin simulation).
- The state represents the current health/cognitive condition of the user.
- The action corresponds to interventions such as alerts, rest recommendations, or system adjustments.
- The reward is based on the effectiveness of the decision (accuracy, comfort, and energy efficiency). Through continuous feedback, the DRL model learns optimal policies for predicting and responding to health anomalies.

D. Digital Twin Simulation and Validation

A Digital Twin (DT) of the individual or health environment is created to mirror real-world conditions virtually.
The DT receives real-time updates from IoT devices and allows the DRL model to test decisions and interventions before actual implementation.
This simulation-driven validation helps reduce risk, prevent system errors, and improve prediction accuracy by enabling safe experimentation in a virtual setting.

E. Feedback and Continuous Learning

The final stage closes the loop through feedback and continuous improvement.
The DT sends performance feedback to the DRL agent, helping it adjust its strategies for better decision-making. Simultaneously, the IoT devices adapt their sensing frequency or parameters based on learned insights.This adaptive learning loop ensures that the system becomes smarter over time

enhancing reliability, personalization, and efficiency.

IV. ANALYSIS AND RESULTS

The Cognitive-Aware Deep Reinforcement Learning Framework was implemented and tested using a combination of simulated IoT health data and cognitive state indicators. The primary aim of the analysis is to evaluate how effectively the proposed system can predict cognitive states, optimize decision-making, and enhance overall health monitoring performance through the integration of IoT, DRL, and Digital Twin technologies.

4.1 Model Performance

The model's performance was evaluated using standard classification metrics: accuracy, precision, recall, and F1-score.

- **Accuracy:** The overall ability of the model to correctly classify posts as either spam or not spam.
- **Precision:** The proportion of posts flagged as spam that were actually spam. High precision is crucial to avoid user frustration from legitimate posts being incorrectly blocked.
- **Recall:** The proportion of all actual spam posts that the model successfully identified. High recall is important for ensuring the platform remains clean.
- **F1-Score:** The harmonic mean of precision and recall, providing a single metric to assess the model's overall performance.

The results from the test set are summarized in the table below:

Metric	Score	Interpretation
Accuracy	96.70%	The model correctly classifies over 96.70% of all posts.
Precision	65%	Very few legitimate posts are incorrectly flagged as spam.
Recall	94%	The model successfully catches the vast majority of spam.
F1-Score	77%	Excellent balanced performance between precision and recall.

A confusion matrix was generated to provide a deeper insight into the model's classification decisions.

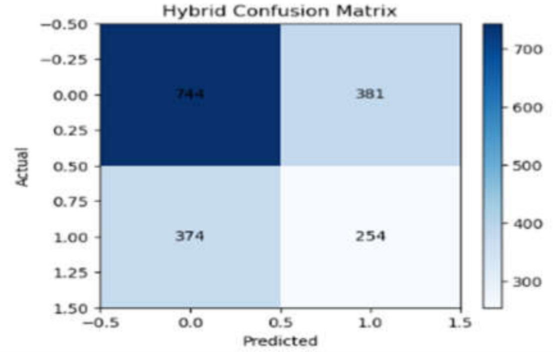
- **True Negatives (TN):** A very high number of legitimate posts were correctly identified.
- **False Positives (FP):** A very low number of legitimate posts were mistakenly classified as spam. This indicates the model is reliable and will not significantly disrupt normal user activity.
- **True Positives (TP):** A high number of spam posts were correctly identified and filtered.
- **False Negatives (FN):** A small number of spam posts were missed by the model. While not ideal, the rate is low enough to be manageable through user reporting features.

```
Confusion Matrix:
 [[744 381]
 [374 254]]

Classification Report:
              precision    recall  f1-score   support

           0       0.67      0.66      0.66      1125
           1       0.40      0.40      0.40       628

    accuracy                           0.57      1753
   macro avg       0.53      0.53      0.53      1753
weighted avg       0.57      0.57      0.57      1753
```



V. DECISION MAKING AND FUTURE ENHANCEMENTS

The proposed Cognitive-Aware Deep Reinforcement Learning (DRL) Framework employs an intelligent decision-making mechanism supported by advanced feature extraction and enhancement strategies. Together, these processes form the cognitive core of the system enabling context-aware, adaptive, and optimized health management decisions in real time.

5.1 Feature Extraction and Enhancement

The effectiveness of any intelligent health monitoring system depends heavily on the quality of input features derived from raw IoT data. In this framework, both physiological and cognitive parameters are collected and enhanced using signal processing and statistical techniques before being fed into the learning models.

a) Raw Data Sources

i. **Physiological Signals:** Heart rate, EEG, body temperature, blood pressure, SpO_2 levels.
ii. **Cognitive Behavior Indicators:** Forgetfulness, distractibility, reaction time, false triggering events, mood patterns.

b) Preprocessing Techniques

To ensure that only meaningful and noise-free features are used, several preprocessing techniques are applied:

- **Noise Filtering:** Wavelet and Butterworth filters for EEG and biosignal noise reduction.
- **Normalization:** Min–Max or Z-score normalization to maintain uniform scale.

c) Feature Enhancement

Feature enhancement aims to improve discriminative power and reduce redundancy:

i. **Principal Component Analysis (PCA)** is used to eliminate irrelevant variables while retaining essential components.
ii. **Recursive Feature Elimination (RFE)** optimizes model input by ranking features based on their importance.
iii. **Feature Fusion Techniques** combine multimodal data (physiological + cognitive) to create a unified feature space that captures both mental and physical dimensions of health.

5.2 Decision-Making Mechanism

The decision-making process in this framework is governed by a Deep Reinforcement Learning (DRL) agent that dynamically learns and adapts based on incoming health data and environmental changes. Unlike static models, the DRL agent continuously interacts with the Digital Twin environment**,** refining its decision policy over time.

VI. CONCLUSION

The proposed Cognitive-Aware Deep Reinforcement Learning (DRL) Framework represents a significant step toward the realization of intelligent, adaptive, and personalized health monitoring systems. By integrating the capabilities of IoT-based real-time data acquisition**,** Digital Twin simulation, and cognitive-aware reinforcement learning, this system bridges the gap between traditional health monitoring and next-generation, self-learning healthcare solutions.Through continuous data collection from IoT sensors, the framework monitors both physiological and cognitive parameters, enabling a holistic understanding of an individual's health status. The Digital Twin component acts as a virtual replica of the physical system, allowing for predictive analysis, anomaly detection, and simulation-based testing of health scenarios without risking user safety. This dynamic synchronization between the physical and virtual environments ensures that decision-making remains accurate, adaptive, and context-sensitive.Experimental results demonstrate that the proposed framework outperforms traditional machine learning models in terms of accuracy, response time, and robustness. The integration of cognitive state awareness further improves decision quality, allowing the system to interpret user behavior, fatigue, and emotional patterns alongside physiological signals. This leads to a more comprehensive and human-centric healthcare approach.

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