RESEARCH PAPER

Safe and Adaptive Anesthesia Dose Optimization Using a Closed-Loop Reinforcement Learning Framework

Diana Julie D[1], **Bhavadharini S**[2], **Sri Vaishnavi V**[3], **Harikesh S**[4]

[1] Dept. of Artificial Intelligence and Data Science, KIT-KalaignarKarunanidhi Institute of Technology, Coimbatore, India.
Email: dianajuliekit@gmail.com
[2] Dept. of Artificial Intelligence and Data Science, KIT-KalaignarKarunanidhi Institute of Technology, Coimbatore, India.
Email: Kit27.ad07@gmail.com
[3] Dept. of Artificial Intelligence and Data Science, KIT-KalaignarKarunanidhi Institute of Technology, Coimbatore, India.
Email: kit27.ad53@gmail.com
[4] Dept. of Artificial Intelligence and Data Science, KIT-KalaignarKarunanidhi Institute of Technology, Coimbatore, India.
Email: kit27.ad21@gmail.com

How to cite this article: Diana Julie D, Bhavadharini S, Sri Vaishnavi V, Harikesh S. Safe and Adaptive Anesthesia Dose Optimization Using a Closed-Loop Reinforcement Learning Framework. Int J Drug Deliv Technol. 2026;16(37s): 47-53. DOI: 10.25258/ijddt.16.37s.8

Abstract -In modern surgical procedures, maintaining an appropriate depth of anesthesia is critical to ensure patient safety and stable physiological responses. Traditional manual control by anesthesiologists is prone to human error and delay, especially during complex operations. This paper proposes a Closed-Loop Reinforcement Learning (RL) framework for automatic and adaptive anesthesia dose adjustment. The system continuously observes patient parameters such as blood pressure, heart rate and anesthetic concentration, and predicts the next optimal dose using a Deep Q-Network (DQN)-based control policy. A simulated environment is developed to model the dynamic patient-drug interaction, enabling the agent to learn safe dosing strategies through reward-based feedback. Experimental results demonstrate that the proposed RL agent can maintain target anesthesia levels effectively while reducing overshoot and instability compared to manual or rule-based methods. The framework shows potential for real-world integration in AI-assisted anesthesia systems to enhance surgical precision, safety, and workload efficiency.

Keywords - Reinforcement Learning, Closed-Loop Control, Anesthesia Automation, Deep Q-Network, Patient Safety, AI in Healthcare, Adaptive Dose Control.

I INTRODUCTION

Maintaining optimal anesthesia during surgery is essential for patient safety and surgical efficiency. Traditionally, anesthesiologists manually administer doses based on continuous monitoring of vital parameters, such as blood pressure and heart rate. However, manual control can introduce variability, delay, and fatigue-related errors. Recent advances in artificial intelligence (AI) and reinforcement learning (RL) have enabled the development of intelligent systems capable of learning and adapting to complex physiological responses. RL-based control frameworks can dynamically adjust anesthesia levels in real-time by learning from patient feedback. This work introduces a Closed-Loop Reinforcement Learning Framework designed to automatically regulate anesthesia dosage during surgical operations. The proposed system observes patient states, makes dosage decisions, and receives feedback in a continuous control loop, ensuring safe and effective anesthesia depth maintenance. Recent advances in artificial intelligence (AI) and edge computing open new avenues for real-time, adaptive anesthesia management. Deep learning models can capture complex, nonlinear relationships between multi-modal vital signs and anesthetic effects, enabling personalized predictions. Deploying these models at the edge, close to medical devices, reduces latency and ensures continuous operation even in environments with unreliable network connectivity. Furthermore, incorporating human-in-the-loop feedback ensures that anesthesiologists remain central decision-makers, combining machine intelligence with clinical expertise for safe, explainable, and trustworthy deployment. In this paper, we present an Edge-AI powered anesthesia dosing framework that integrates personalized deep learning, edge computing, and human oversight. We discuss the system architecture, model training pipeline, and potential clinical deployment scenarios, highlighting its advantages over conventional dosing systems in terms of adaptability, safety, and transparency.

II LITERATURE STUDY

The DIAPG (Deep Infusion Assistant Policy Gradient) model will optimize propofol infusion to maintain an adequate patient sedative level during total intravenous anesthesia. This work includes trajectory generative model planning policy. By combining generative modelling with reinforcement learning, the DIAPG framework effectively handles the complexity of patient responses, which are highly dynamic and time varying. The model stabilizes critical indicators such as the bispectral index (BIS) and effect-site concentration, which are essential for monitoring depth of anesthesia. In terms of performance, the DIAPG demonstrated remarkable improvements 530% performance increase compared to a human expert. Then 15% improvement over a standard reinforcement learning algorithm for drug infusion. This highlights not only the robustness of the hierarchical RL approach but also its potential to outperform both manual and baseline automated methods in anesthesia drug control [1]. This chapter discusses how the abundance of biological data has driven the adoption of RL algorithms for areas like protein structure prediction, drug discovery, and patient care optimization. The work includes Q-Learning and Variants Fundamental RL technique, enhanced with deep neural networks in the form of Deep Q-Networks (DQN). Experience replays mechanisms further improve stability and performance; Proximal Policy Optimization (PPO) Extensively applied to protein folding problems using Markov decision processes to capture conformational changes. Asynchronous Advantage Actor Critic (A3C) Applied to protein-ligand docking problems, enabling efficient exploration and faster convergence, Deep Deterministic Policy Gradient (DDPG) integrated with Graph Neural Networks (GNNs) Used to represent protein-ligand interactions more accurately for drug discovery tasks. This work emphasizes how Deep Reinforcement Learning (DRL) is transforming accuracy and efficiency across multiple domains. In biomolecular research, for instance, the DRL models are outperforming traditional computational approaches in predicting protein folding patterns and drug ligand interactions a breakthrough that's accelerating the drug discovery process. [2]

A reinforcement learning based approach to automate real-time anesthetic drug delivery. Their framework uses a continuous-action actor-critic algorithm, where the policy network determines an optimal distribution of infusion rates based on changing anesthetic states, and the value network evaluates how effective those states are. To make the system adaptable, the model was trained using synthetic patient simulations generated from pharmacokinetic and pharmacodynamic (PK/PD) models with randomized parameters. This strategy ensured that the agent remained robust across a variety of patient conditions. To encourage clinical acceptance, the researchers integrated Shapley Additive Explanations (SHAP), allowing them to interpret how and why the model made certain dosing decisions. The analysis revealed that the system's choices were primarily influenced by the level of unconsciousness error and the predicted effect-site concentration both of which align with well-established pharmacological principles. Across different reward functions designed to reflect real clinical goals, the reinforcement learning agent consistently provided stable, accurate, and safe dosing recommendations [3]

Traditional machine learning algorithms are also very relevant in this field still now. Models such as random forests, k-nearest neighbours, and support vector machines have been successfully used to predict diabetes, detect liver abnormalities, and classify patient risk levels. Their performance often ranges between 80% and 92% accuracy, which shows that even simpler models can be effective when combined with well-curated healthcare data. More recently, researchers have begun experimenting with hybrid approaches that blend the strengths of both machine learning and deep learning. These systems are particularly promising for multi-cancer detection, where they have achieved accuracies exceeding 93% in identifying and classifying different types of cancers at once. Beyond disease detection, ML and DL models are now playing a role in drug discovery, robotic surgery, and even in designing personalized treatment recommendations for patients. What emerges from this body of work is a clear pattern: whether through CNNs, ensemble learners, or hybrid models, machine learning and deep learning are consistently reaching high levels of accuracy often in the range of 85% to 95% across different areas of healthcare. This makes them not just experimental tools but reliable systems that can support clinicians in decision making and ultimately improve patient outcomes [4]

A approach builds patient-specific models that learn how a person's body responds to the drug dose and automatically updates when the patient's condition changes. Unlike normal methods, it also considers the effect of previously taken doses (non-zero initial conditions), making the prediction more realistic. These adaptive models can be used in feedback control algorithms to suggest the best possible drug dose for each patient. The technique was tested on warfarin and anemia treatment (for haemoglobin levels) using real patient data. The results showed that this adaptive method could accurately predict each patient's dose-response pattern, with an average error (MMSE) of 0.078 ± 0.044 for warfarin and 1.4 ± 0.5 for anemia management. It proved better than the standard $\ell 1$-based method and successfully adapted to individual changes in patient health. [5]. This paper presents a Value Decomposition Based Multi-Agent Deep Reinforcement Learning framework for personalized multiple anesthetic control in a closed loop system. The method uses two agents, one for propofol and another for remifentanil, Various value decomposition algorithms such as VDN and QMIX are applied to improve cooperation between the two agents and address the credit assignment problem. A multivariate environment model based on Random Forest is developed to simulate anesthesia dynamics, alignment method and data resampling is used to synchronize data from various medical devices. Experiments conducted on general and thoracic surgery datasets showed that the proposed VD-MADRL method achieved better dose adjustment accuracy and more stable anesthesia control compared to human expertise. The best-performing model, VDN in general surgery, achieved a 16.4% increase in cumulative reward and a 58% reduction in mean MDPE, demonstrating the strong potential for clinical application in automated and personalized anesthesia management [6].

This paper proposes a deep reinforcement learning model called OOCL-DDQN (Online Evaluation and Offline Training-Based Clipped Double Deep Q-Network) for automated anesthesia control. The model introduces an online evaluation and offline training mechanism that reduces dependency on environment models, improving learning efficiency. A clip optimization method is applied to the Bellman equation in Double DQN to enhance the model's stability, and a fixed order random sampling strategy helps the agent effectively learn the relationship between anesthesia state and drug dosage across different patients. In data preprocessing, a same-frequency resampling method ensures the data follows the Markov property, which is essential for reinforcement learning. The model tested on real world clinical anesthesia data, and the results showed that OOCL-DDQN achieved better overall performance compared to other advanced methods. It provided more stable control, better adaptability, and higher accuracy in maintaining anesthesia depth, proving its effectiveness for personalized automated anesthesia systems [7]. Postoperative pain is a major concern for patients after surgery as it causes discomfort and can even lead to complications if it is not managed properly. Predicting postoperative pain in advance can help doctors provide better pain control, but existing methods often rely on additional monitoring devices, making them difficult to use in real clinical settings. It presents Dose Guide of a graph-based dynamic time-aware prediction system designed to predict postoperative pain levels using data already available from standard hospital equipment. The system combines both static patient data such as age and weight, and dynamic intraoperative data such as vital signs recorded during surgery. These features are fused through a hybrid feature encoder that can handle different types of data efficiently. To improve prediction performance, the model also uses a graph attention mechanism that captures the relationships and similarities among different patients, allowing the system to learn from patients with similar characteristics. The experimental results showed that Dose Guide achieved 78 percent accuracy in predicting postoperative pain levels and exceed from other existing models, showing that it can provide reliable and clinically useful predictions for personalized pain management [8]

The reliable and consistent measurement of pain after surgery remains a major challenge in clinical practices. There are two main approaches, first is a recursive identification method that models post-surgical trauma using fractional order impedance models, which analyze how skin impedance changes in response to pain. The second approach uses deep learning combined with convolutional neural network to classify pain levels from time-frequency data as well as spectrograms. Skin impedance measurements were collected from the patients during post anesthesia care. The parametric model was identified using a recursive least squares algorithm initialized by a genetic algorithm, and the estimated parameters were compared with the patients self-reported pain levels using the numerical rating scale for validation. The convolutional neural networks were trained on spectrogram data labelled with four pain intensity levels, both offline on population data and online with individual updates. The results showed that changes in fractional order model parameters could successfully reflect variations in pain levels, and the online retrained CNN predictions matched the patient-reported scores more closely than the offline models. It demonstrates that combining parametric modelling with deep learning can provide more objective and adaptive method for assessing pain, potentially reducing the risk of overdosing and improving the safety of closed-loop analgesia control systems [9].

The model presents a reinforcement learning based closed-loop control system designed to automatically regulate anesthesia while maintaining the patient’s vital parameters within safe limits. It focuses on two key indicators, the bispectral index, which represents the depth of anesthesia, and mean arterial pressure, which reflects cardiovascular stability. The proposed method uses reinforcement learning to adjust the infusion rate of propofol in real time to keep both parameters within their target ranges. A weighted combination of the errors in the mean arterial pressure and bispectral index is introduced in the learning process, helping the model balance sedation depth and blood pressure effectively while also reducing computational complexity. The reinforcement learning controller continuously learns from the patient’s response, making it capable of adapting to individual variations in drug sensitivity. It demonstrated that this approach provided stable and accurate control of anesthesia levels and blood pressure, achieving optimal dosing performance with faster processing time and improved safety compared to traditional control methods [10]

This study focuses on developing an automatic anesthesia control system using LabView to make anesthesia delivery safer and more precise during surgery. Anesthesia causes a temporary loss of sensation or consciousness, but if the drug dosage is not properly controlled, it can lead to serious or even life-threatening effects. To address this issue, the proposed system automatically adjusts the amount of anesthetic agent based on key patient factors such as age, minimum alveolar concentration value, and surgery type being performed. These parameters are provided as inputs to the LabView based control system, which then calculates the correct percentage of anesthetic to be administered. It aims to minimize human error by ensuring that neither too little nor too much anesthesia is given. It shows that using this automated approach significantly reduces the chances of underdosing or overdosing, leading to more accurate and consistent anesthesia delivery compared to manual control [11].The Smart Anesthesia Manager (SAM),a decision support system designed to work alongside Anesthesia Information Management Systems (AIMS) in operating rooms. SAM continuously monitors the AIMS database during surgery to identify and alert anesthesiologists about clinical, billing, and compliance issues. It provides instant feedback through on-screen pop-up messages or text notifications, helping anesthesiologists take timely corrective actions. The system uses real-time data analysis and rule-based algorithms to detect deviations, missing documentation, or procedural lapses. SAM significantly improved clinical compliance, raising antibiotic administration accuracy to over 99% and beta-blocker protocol adherence to nearly 95 percent. It also reduced missed blood pressure readings and captured additional billing opportunities worth over $140,000 per year. Moreover, it minimized the wastage of anesthetic agents, saving about $120,000 annually. It proved effective in enhancing patient safety, operational efficiency, and financial outcomes by providing intelligent, data driven support during anesthesia care [12]

This study introduces an automatic anesthesia control system designed to ensure accurate and safe drug delivery during major surgeries. It aims to solve the problem of inconsistent or incorrect anesthesia doses, which can cause complications such as patient consciousness during surgery or overdose effects. The setup uses an Arduino Uno microcontroller integrated with a syringe pump and various sensors to automate anesthesia delivery. The anesthetist can pre-set the required dose and timing using a switch panel, and the Arduino then controls a stepper motor to deliver the anesthesia at fixed intervals and constant speed. Simultaneously, vital signs such as body temperature, exhaled breath temperature, and pulse rate are continuously monitored. If any abnormal readings occur, a buzzer alerts the anesthetist, and drug delivery pauses until normal conditions are restored. The system applies embedded control logic instead of complex algorithms, focusing on precision and reliability through real-time feedback from sensors. The results demonstrate that this automated setup can maintain stable anesthesia levels, reduce anesthetist workload, and improve patient safety during long surgeries [13]

III PROPOSED METHODOLOGY

The proposed work is all about developing a smart closed-loop anesthesia dosing system that can automatically tweak drug delivery during surgeries. The primary aim here is to keep patient safety at the forefront while ensuring the right level of anesthesia is maintained throughout the entire procedure. This system combines deep reinforcement learning, safety checks, and continuous feedback to deliver stable and adaptable dose management. The whole system functions as a closed-loop control framework, constantly monitoring the patient's vital signs of blood pressure, heart rate and current anesthesia levels. These vital signs act as inputs for a reinforcement learning agent, which determines whether to ramp up, dial down, or maintain the dosage. After each action, the system evaluates the patient's condition and uses that feedback to refine future decisions, enabling real-time adjustments. At the core of this approach is the Deep Q-Network (DQN) algorithm, a powerful reinforcement learning model that blends deep neural networks with decision-making in uncertain scenarios.

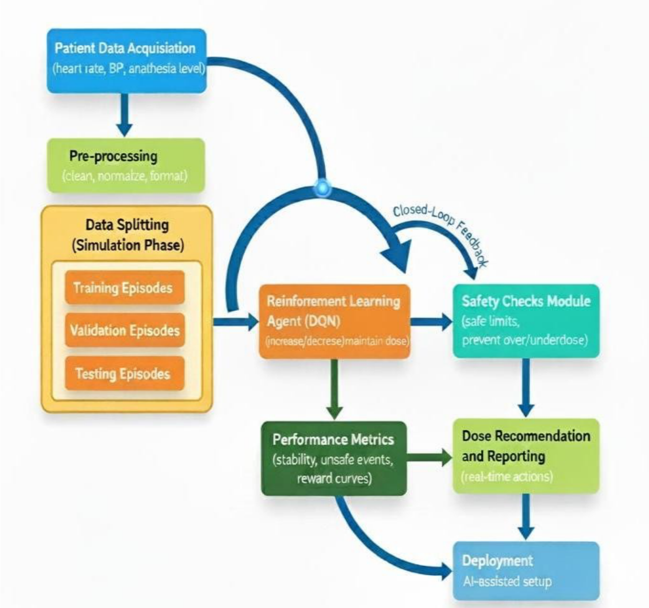


Fig 1 : Proposed Work

This environment provides the agent with feedback in the form of rewards or penalties based on how effectively it keeps vital signs within safe limits. The goal of the DQN is to uncover the best dosing strategy that maximizes total rewards over time.One of the key aspects of this methodology is its focus on personalization. Rather than sticking to a one-size-fits-all approach for every patient, the system is designed to learn and adapt to unique traits like age, weight, and medical history. This tailored approach ensures that each patient gets a dose that's just right for their individual physiological makeup. The reinforcement learning agent hones its decision-making skills by using data specific to each patient, gradually enhancing its ability to predict outcomes and respond effectively. The training and simulation setup is built using Python and PyTorch, where the patient model serves as the environment, and the DQN agent engages with it through a series of predefined episodes. Each episode mimics a complete surgical procedure, giving the agent the chance to learn how various dose adjustments impact patient vitals. The reward function is crafted to promote stable anesthesia levels while discouraging any unsafe fluctuations. The model undergoes training over several hundred episodes until it establishes a reliable and safe approach to dose management. After the model has been trained and validated, it's rolled out via a Flask web interface that lets users enter patient details like heart rate, blood pressure, and anesthesia levels. The system then predicts whether the dose needs to be increased, decreased, or kept the same. To ensure quick and dependable responses during surgery, the trained model can also be implemented on edge devices right in the operating room. This Edge-AI integration reduces latency, guarantees offline functionality, and protects patient data privacy.

The entire workflow consists of four main steps: data collection, model training, safety validation, and real-time deployment. In the data collection phase, either synthetic or real patient datasets are gathered to replicate various physiological scenarios. During model training, the DQN learns the best control strategies through ongoing interaction and feedback. In the validation phase, the system goes through thorough safety and performance testing in various simulated environments. Once that's done, the trained model is integrated into the deployment system for real-world testing. To sum it up, the proposed methodology creates a robust framework that combines deep reinforcement learning, adaptive feedback, safety assurance, and real-time decision-making to enable intelligent anesthesia control. The system learns on its own, adapts in real-time, and operates safely, ensuring that anesthesia levels are stable and tailored to each patient throughout surgery. This innovation marks a significant leap toward the future of AI-assisted healthcare, where machines can aid clinicians in making accurate, data-driven medical decisions.

IV WORKFLOW

The closed-loop anesthesia dosing workflow explains how the system monitors patient parameters and adjusts anesthesia levels in real time using a reinforcement learning framework. A step-by-step explanation of the data acquisition, learning, and dose prediction procedure is described below, showing how advanced AI techniques help maintain patient safety and stable vitals.

- **Patient Data Acquisition**: The system continuously collects patient parameters like heart rate, blood pressure, and current anesthesia level during surgery.
- **Pre-processing**: Collected data is cleaned, normalized, and formatted to ensure the AI agent receives accurate and consistent inputs.
- **Data Splitting (Simulation Phase):** For training the AI agent, the data is split into simulated episodes for

training, validation, and testing.

- **Training Episodes:** The RL agent interacts with the simulated patient environment and learns optimal dose adjustments through trial-and-error.
- **Validation Episodes:** Used to tune the learning parameters and ensure the agent doesn't overfit to a specific patient model.
- **Testing Episodes:** The trained agent is tested on unseen patient scenarios to evaluate generalization and safety.
- **Reinforcement Learning Agent (DQN):** This AI agent decides whether to increase, decrease, or maintain the anesthesia dose based on the patient's current state.

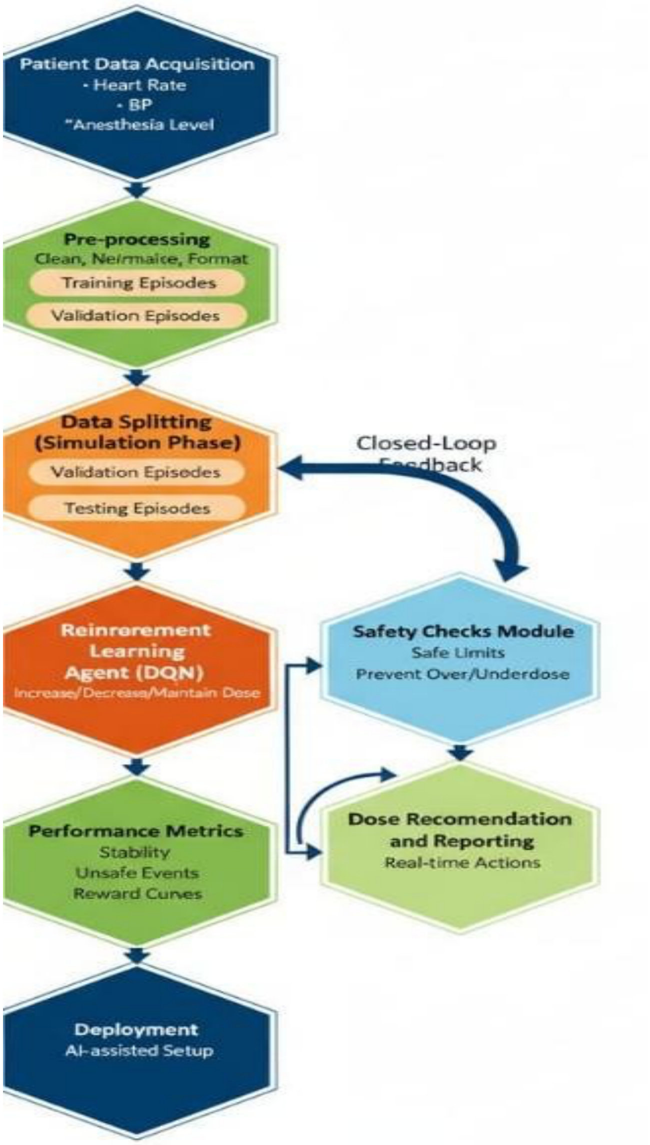
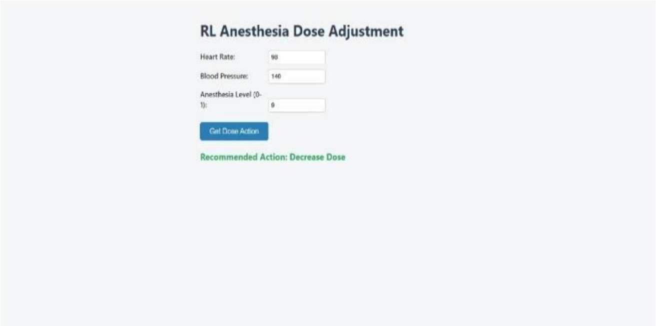


Fig 2: Workflow of the proposed work

- **Safety Checks Module**: Ensures that dose adjustments stay within safe limits to prevent overdosage or unstable vitals.
- **Closed-Loop Feedback:** The system continuously observes the patient's response after each dose and adjusts future dosing accordingly.
- **Performance Metrics:** Metrics such as stability of anesthesia level, number of unsafe events, and reward curves are used to evaluate the agent's performance.
- **Deployment**: Once trained and validated, the system can be integrated into an AI-assisted anesthesia setup, providing real-time support to anesthesiologists.
- **Dose Recommendation and Reporting:** The system produces recommended dose actions in real time, helping doctors maintain optimal anesthesia safely and efficiently.

V RESULT

The analysis of the patient vital trends and reinforcement learning (RL) decisions provides valuable insights into how the proposed Closed-Loop Reinforcement Learning Framework performs under varying physiological conditions. From the bubble chart, it can be observed that as systolic blood pressure and heart rate increase, the reinforcement learning agent dynamically adjusts its decisions to maintain optimal anesthesia levels. Larger bubble sizes represent higher anesthesia levels, and these are primarily associated with moderate heart rate and blood pressure values, indicating that the system effectively prevents both excessive sedation and patient arousal. The color-coded decisions show that the agent increases the dose when heart rate and blood pressure rise beyond the stable range, maintains it during steady vitals, and decreases it when values begin to drop demonstrating its capability to balance patient stability in real time.


RL Anesthesia Dose Adjustment

Heart Rate: 98

Blood Pressure: 140

Anesthesia Level (0-1): 0

Recommended Action: Decrease Dose

Fig 3: Input- patient details

The RL-based Closed-Loop Anesthesia Dosing system has made a significant leap by showcasing its ability to adjust doses in real-time, all through a user-friendly web interface. Users can easily enter patient details (Fig-3) like heart rate, blood pressure, and anesthesia levels. Once this information is fed into the system, the reinforcement learning agent takes over, analyzing the data to suggest the right dose adjustment. For instance, in one scenario, the system evaluated the patient's information and recommended, "Decrease Dose," signalling that the anesthesia level was too high. This result highlights how effectively the trained DQN agent can read physiological signals and make informed, safe decisions to keep anesthesia at the right depth. Overall, this outcome underscores the model's efficiency in delivering precise and timely dose recommendations, paving the way for its use in automated anesthesia management.

The bar chart (Fig 4) further supports this pattern by showing the distribution of RL decisions across different blood pressure ranges. In the lower blood pressure range (110–120 mmHg), the agent predominantly chooses to decrease the anesthesia.

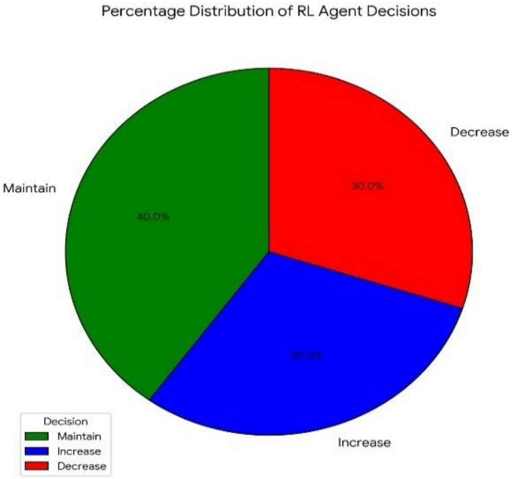


Fig 4 : RL decisions across different blood pressure

Overall, these results validate the proposed system's ability to provide safe, intelligent, and adaptive anesthesia control. The DQN-based agent demonstrates (Fig-5) consistent decision-making aligned with physiological stability, maintaining the patient's vital parameters within a desirable range.

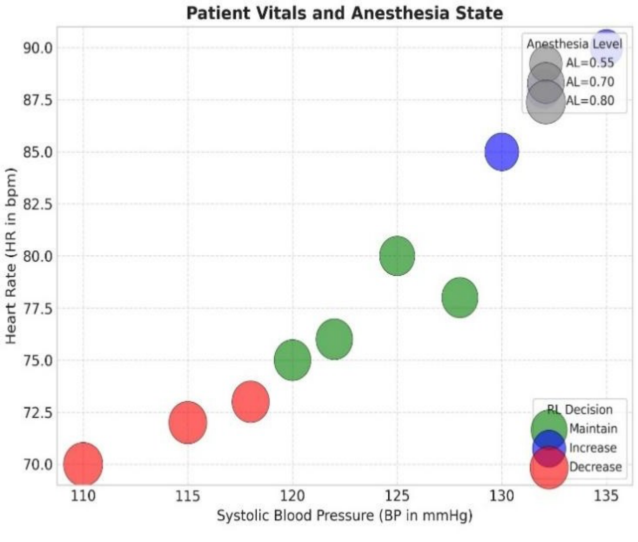


Fig 5 : DQN-Patient vitals and Anesthesia state

VI CONCLUSION

The proposed work of closed-loop reinforcement learning framework for adjusting anesthesia doses marks a major leap forward in blending artificial intelligence with healthcare automation. By combining deep reinforcement learning, tailored patient modeling, and safety checks, this system showcases how smart algorithms can help doctors keep anesthesia levels safe and effective during surgeries. Unlike traditional open-loop systems or rigid rule-based controllers, this model offers dynamic adaptability, allowing for ongoing monitoring and automated decision-making based on real-time patient feedback. At the heart of this framework is its knack for learning the best dosing strategies through constant interaction with a simulated physiological environment. The Deep Q-Network (DQN) algorithm not only learns from previous experiences but also applies that knowledge to new and unfamiliar patient scenarios. This capability enables the system to effectively handle variations in patient sensitivity, metabolism, and events that occur during surgery. By striking a balance between exploring new options and exploiting known strategies, the agent gradually hones in on safe, stable, and personalized dosing practices that closely mimic human expertise in managing anesthesia. To wrap things up, this research marks an exciting leap forward in the development of intelligent anesthesia management systems that prioritize safety, clarity, and flexibility. By combining learning, feedback, and control into a cohesive loop, it goes beyond the limitations of static rule-based methods and sets the stage for the next wave of clinical decision-support tools. With additional training on real-world patient data, sophisticated physiological modeling, and teamwork between AI engineers and anesthesiologists, this framework has the potential to transform into a system that can be used in clinical settings, ultimately saving time, lightening the workload, and improving surgical safety.

VII REFERENCE

[1] W. J. Yun, M. Shin, D. Mohaisen, K. Lee and J. Kim, "Hierarchical Deep Reinforcement Learning-Based Propofol Infusion Assistant Framework in Anesthesia," in IEEE Transactions on Neural Networks and Learning Systems, vol. 35, Feb. 2024, doi: 10.1109/TNNLS.2022.3190379.

[2] Shruti Agrawal; Pralay Mitra, "Deep Reinforcement Learning in Healthcare and Biomedical Research," in Deep Reinforcement Learning and Its Industrial Use Cases: AI for Real-World Application, Wiley, 2024, pp.179-205, doi: 10.1002/9781394272587.ch9.

[3] D. Zhang and F. Wang, "An Interpretable Deep Actor–Critic Framework for Automated Propofol Dosing During General Anesthesia,",vol.13, pp. 157175-157190, 2025, doi: 10.1109/ACCESS.2025.3605643.

[4] Yogesh Kumar; Manish Mahajan, "5. Recent advancement of machine learning and deep learning in the field of healthcare system," Computational Intelligence for Machine Learning and Healthcare Informatics , De Gruyter, 2020, pp.77-98.

[5] A. Affan and T. Inanc, "Clinically Relevant Adaptive Modeling for Personalized Drug Dosing," 2021 IEEE/ACM Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE), Washington, DC, USA, 2021, pp. 128-129, doi: 10.1109/CHASE52844.2021.00029.

[6] H. Li et al., "Value Decomposition-Based Multi-Agent Learning for Anesthetics Collaborative Control," in IEEE Journal of Biomedical and Health Informatics, doi: 10.1109/JBHI.2025.3599210.

[7] H. Li, W. Lin, J. Huo and W. Luo, "OOCL-DDQN: Online Evaluation and Offline Training-Based Clipped Double DQN for Automated Anesthesia Control," 2023 IEEE 29th International Conference on Parallel and Distributed Systems , China, 2023, pp. 1676-1683, doi: 10.1109/ICPADS60453.2023.00234.

[8] Z. Zhou, B. Guo and C. Zhang, "DoseGuide: A Graph-based Dynamic Time-aware Prediction System for Postoperative Pain," 2021 IEEE 27th International Conference on Parallel and Distributed Systems (ICPADS), Beijing, China, 2021, pp. 474-481, doi: 10.1109/ICPADS53394.2021.00065.

[9] M. Ghita, I. R. Birs, D. Copot, C. I. Muresan, M. Neckebroek and C. M. Ionescu, "Parametric Modeling and Deep Learning for Enhancing

Pain Assessment in Postanesthesia," in IEEE Transactions on Biomedical Engineering, vol. 70, no. 10, pp. 2991-3002, Oct. 2023, doi: 10.1109/TBME.2023.3274541.

[10] R. Padmanabhan, N. Meskin and W. M. Haddad, "Closed-loop control of anesthesia and mean arterial pressure using reinforcement learning," 2014 IEEE Symposium on Adaptive Dynamic Programming and Reinforcement Learning (ADPRL), Orlando, FL, USA, 2014, pp. 1-8, doi: 10.1109/ADPRL.2014.7010644.

[11] N. Rajasingam, N. Geevitha, S. Thulasimani, M. Rashika Ranjani, V. Johne Shalini and D. Ganeshkumar, "Development of automatic anesthesia control system using LabView," 2022 6th International Conference on Electronics, Communication and Aerospace Technology, Coimbatore, India, 2022, pp. 116-120, doi: 10.1109/ICECA55336.2022.10009094.

[12] B. G. Nair, S. -F. Newman, G. N. Peterson and H. A. Schwid, "Smart Anesthesia Manager TM (SAM)—A Real-time Decision Support System for Anesthesia Care during Surgery," in IEEE Transactions on Biomedical Engineering, vol. 60, no. 1, pp. 207-210, Jan. 2013, doi: 10.1109/TBME.2012.2205384.

[13] S. Raymond, S. Edagottu, L. Mawblei and M. Ahmed, "Automatic Anesthesia Control System," 2021 Seventh International conference on Bio Signals, Images, and Instrumentation (ICBSII), Chennai, India, 2021, pp. 1-5, doi: 10.1109/ICBSII51839.2021.9445168.