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Reinforcement Learning-Based Adaptive Therapy Planning for Personalized Healthcare Applications

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ABSTRACT

Individualized healthcare requires dynamic treatment plans which can address the changing conditions of patients and complicated clinical dynamics. The sequential, uncertain, and long-term nature of therapeutic decision-making is constrained in conventional rule-based systems, and in simple predictive models, which rely on short-term predictive statistics. This research suggests a reinforcement learning (RL)-based model of adaptive therapy planning, a Markov Decision Process (MDP) to represent the dynamics of patient states and the treatment actions with time. The states of patients are being built on the basis of longitudinal electronic health record (EHR) data, which includes vital signs, laboratory measurements, and clinical history as well as actions are discrete therapeutic decisions. A Deep Q-Network (DQN) is used to find the best policy of treatment to maximize cumulative clinical good via a reward function that combines the survival outcome, reduction of risk, and effectiveness of treatment. The framework is tested on a benchmark critical care dataset, compared to conventional supervised learning models, such as logistic regression, random forests and LSTM-based methods. Empirical evidence has shown that the RL-based model has a higher success rate, cumulative reward is improved by around 1520 percent and adaptability to patient-specific trajectories is improved. These results emphasize the usefulness of RL in streamlining serial clinical decision-making and clarify its possibilities to be included in the intelligent clinical decision support systems to deliver personalized healthcare.

1. INTRODUCTION

The blistering healthcare systems digitalisation resulted in the popularization of electronic health records (EHRs), which allow creating a set of treatment options with the use of data and individual approach. These are massive, longitudinal data that give copious information on patient courses, clinical actions and outcomes. Nevertheless, the majority of current machine learning models used in healthcare assume the use of fixed prediction models and therefore, clinical decision-making can be discussed as a single-time classification or regression problem. This cannot be represented by such models, which are sequential, time-dependent and uncertain in nature where decisions need to be constantly revised with changing patient conditions [1], [2]. Therapy planning in the practice of real-world clinics is an interactive process incorporating various steps of intervention, feedback and adaptation. The conventional approaches to supervised learning, such as logistic regression and deep neural networks, are not as effective to optimize long-term outcomes because they do not explicitly capture time-dependent effects or delayed actions of interventions [3], [4]. More recent developments in sequential modeling with recurrent neural networks (RNNs) and attention-controlled architectures are to some extent sensitive to temporal dependencies, but do not yet offer a model-based framework to optimize decisions [5], [6]. Reinforcement Learning (RL) has become an effective framework to do sequential decision-making under uncertainty and provides the capability to learn optimal rules to enable the maximization of the cumulative rewards over time [7]. In medicine RL can be used to create a treatment planning as a Markov Decision Process (MDP), where the states of the patient change over time, and treatment actions change over time. In the field of critical care, the use of RL has been shown to have the potential to improve sepsis management [8], intensive care unit decision support [9]. Nevertheless, current RL-based

methods have drawbacks such as a simple form of rewards, a limited usage of longitudinal clinical characteristics, and in-depth comparison with powerful baseline models [10].

To close these gaps, this paper suggests a framework, on the basis of reinforcement learning, to plan adaptive therapy in personalized healthcare application. The proposed method models the treatment decisions in an MDP framework with the patient states based on longitudinal EHR data, and actions based on clinically relevant interventions. Deep Q-Network (DQN) is used to discover the optimal treatment policies to maximize a clinically-informed reward function including the survival outcomes, risk mitigation, and treatment efficiency.

The key findings of this work are as follows:

- Methods: adaptive therapy planning formulation as a Markov Decision Process.
- Creation of a multi-objective reward function that is of clinical interest.
- Deep Q-Network to learn the optimal policy of treatment.
- Extensive testing with respect to the old machine learning and deep learning baselines.

The rest of this paper is formatted in the following way: Section 2 is the review of related work, Section 3 is the proposed methodology section, Section 4 is the description of the experiment setup, Section 5 is the discussion of the results and finally, Section 6 is the conclusion to the paper.

2. RELATED WORK

The recent developments in personalized healthcare addressed the utilization of machine learning to facilitate clinical decision-making on the basis of electronic health records (EHRs). The use of traditional supervised learning models, including logistic regression, support vectors machines, and random forests, have been extensively applied in predicting clinical outcomes, including mortality risk and disease progression [11], [12]. Predictive accuracy has continued to be enhanced with deep learning architectures such as feedforward neural networks and convolutional neural networks which are able to capture intricate nonlinear associations in clinical data [13]. These models, however, generally consider prediction a static activity and do not take into account the temporal and sequential characteristics of treatment choices. Sequential models, like recurrent neural networks (RNNs), Long Short-Term Memory (LSTM) networks, and attention-based models, have been proposed to model longitudinal patient data to deal with the issue of temporal dependencies [14], [15]. Significant methods like the RETAIN and Doctor AI have shown better interpretability and performance in clinical prediction tasks [16]. Although they can be used to model the patterns of time, these methods do not address the mechanism of optimizing sequential treatment policy and are only limited to the prediction of outcomes. The field of Reinforcement Learning (RL) has become an exciting direction in making sequential decisions in healthcare. Deep Q-Networks (DQN) and Actor-Critic systems have been also implemented to optimize the treatment strategies in critical care environments, especially in the managements of sepsis and in ICU treatment [8], [9]. These methods simulate clinical decision-making as a Markov Decision Process (MDP), and such policies can be learned to maximize long-term patient outcomes. Such extensions like Double DQN and Deep Deterministic Policy Gradient (DDPG) have contributed to the enhanced stability and performance of policies [10]. These developments notwithstanding, there are a number of obstacles. To begin with, the design of reward functions is a pressing problem because inadequately structured reward designs may result in clinically unsafe or suboptimal policies [1]. Second, healthcare data can be sparse, noisy, and biased, which restricts the strength and generalizability of the learned models [2]. Third, RL-based systems have interpretability and trustworthiness that persistently act as barriers to clinical adoption [3]. In addition, most of the current research lack detailed benchmarking to strong baseline models, and do not include multi-objective optimization capturing clinical trade-offs in the real world.

This work provides a reinforcement learning-based adaptive therapy planning framework to cope with these limitations by combining structured MDP formulation with a clinically informed reward function. In contrast to the previous methods, the presented model focuses on the sequential decision maximization and detailed comparison with traditional and deep learning benchmarks, which offers a better and more robust and clinically applicable solution to personalized healthcare applications.

3. METHODOLOGY

3.1 Problem Formulation

The planning problem of adaptive therapy is modeled as a sequential decision-making problem based on a Markov Decision Process (MDP) that gives the mathematical model of dynamic and uncertain clinical conditions. The MDP can be defined as a set of states, actions, dynamics of transition, function of the reward and a discount factor that controls the significance of future results as the set as shown in Fig. 1.

$$\square = (S, A, P, R, \gamma) \quad (1)$$

In this definition, the state space is a changing clinical state of a patient in time, and the action space is the therapeutic measures available. The

transition function represents the probabilistic dynamics of patient health states after treatment decisions, and is necessarily stochastic because physiology is variably and treatment response unpredictable. Clinical goals that the reward functionality captures are the improvement in survival, the reduction of complications and cost efficiency. The discount factor guarantees a trade off between short-term and long-term clinical benefits, by enabling the model to prioritize the long-term well-being of patients over the short-term profits.

This model allows the optimization of treatment policies to maximize the cumulative expected reward and consequently makes the decision-making process more aligned with the long-term clinical goals and objectives as opposed to single predictions.

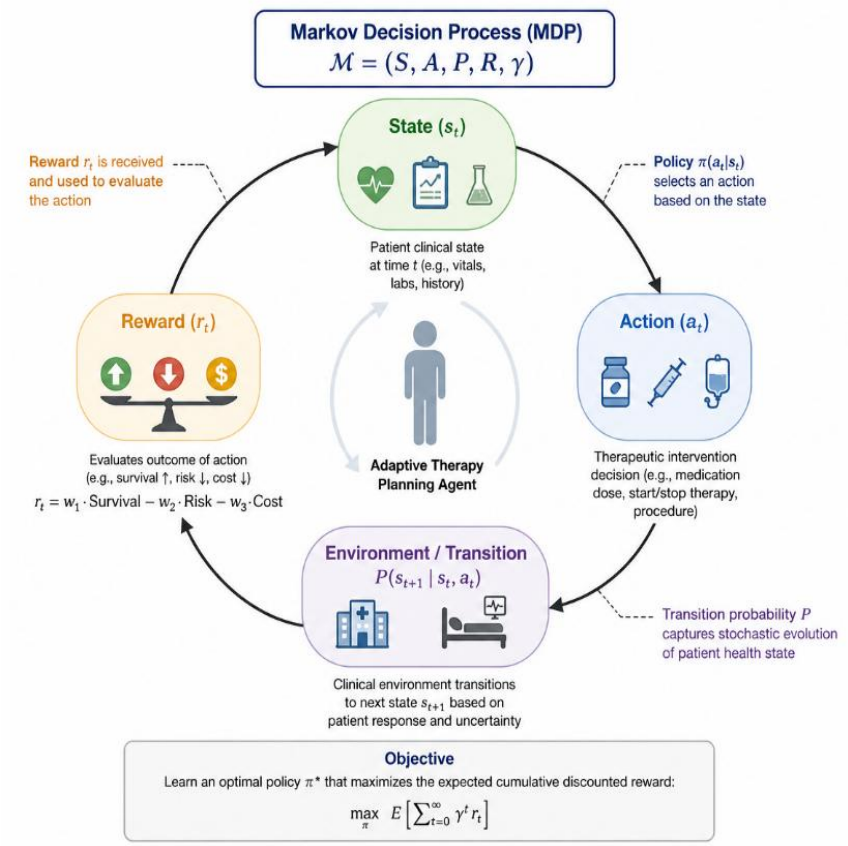


Fig. 1. Markov Decision Process Framework for Adaptive Therapy Planning

3.2 State Representation

Patient states are built out of longitudinal electronic health record (EHR) data, including both static and dynamic clinical characteristics. Each state is modeled as a high-dimensional feature-vector which changes with time in discrete time steps. The representation combines physiological readings like heart rate, blood pressure, respiratory rate, and laboratory examination findings like glucose rates, creatinine, and other bio-markers. Moreover, demographic data, including age and sex are used to give the context of the situation, whereas the past history of treatments is included to outline previous clinical procedures and their impacts, as shown in Fig. 2.

The state during time step tis can be defined as a continuous feature space in n dimensional space:

$$s_t = [x_1, x_2, \ldots, x_n] \quad (2)$$

In order to be robust, missing values of the EHR data are managed by imputation methods and all the features are scaled to be numerically stable during training. Temporal alignment is carried out to harmonize non-uniform clinical measurements to have a uniform state transition between periods.

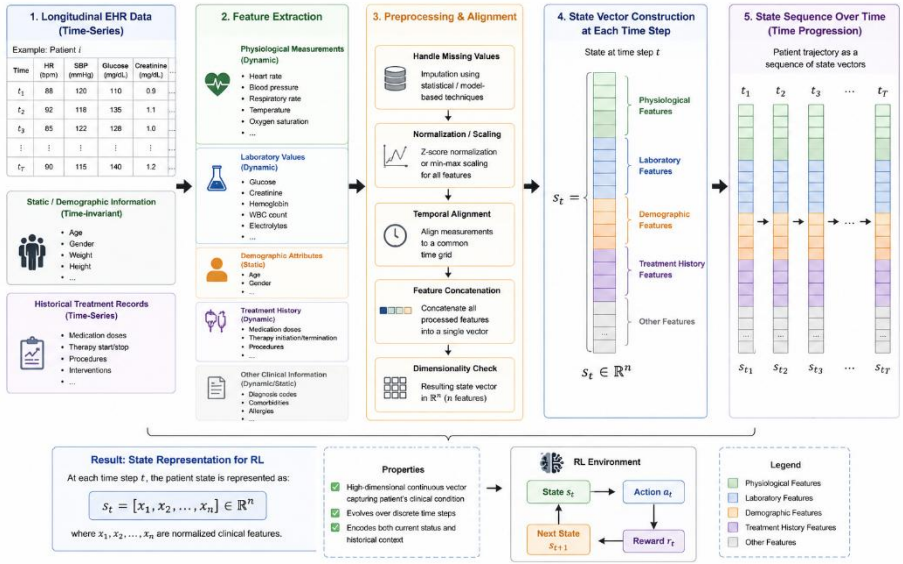


Fig. 2. State Representation from Longitudinal EHR Data for Reinforcement Learning-Based Therapy Planning

3.3 Action Space

Action space is a discrete set of clinically relevant treatment choices. Every action is a potential intervention that may be implemented on the patient in a particular time step. These encompass differences in drug dosage, addition or discontinuation of therapies, and choice in the alternative treatment plans.

$$A = \{a_1, a_2, \ldots, a_k\} \quad (3)$$

To be able to be tractable with the Deep Q-Network framework, the action space must be discretized. Every action should be made to be realistic in clinical choices and enable the policy learned to be interpretable and usable practically. The model makes the assumption that the decisions to be made about treatment are taken on regular basis, which is in line with the clinical supervising cycles.

3.4 Reward Function Design

The reward aspect is an important determinant in the learning process as it measures quality of treatment choices. The reward is developed as a multi-objective function in this study balancing clinical effectiveness, risk reduction and resource utilization:

$$R_t = w_1 \cdot \text{Survival} - w_2 \cdot \text{Risk} - w_3 \cdot \text{Cost} \quad (4)$$

Survival is modeled as an indicator of binary patient outcome (representing survival) and risk is modeled as a likelihood of adverse events or complications as determined by clinical indicators. Cost is a factor of intensity of treatment or healthcare spending. The weighting coefficients are chosen to represent clinical priorities and are optimized empirically in order to have a balanced optimization goal.

Intermediate rewards are allocated in order to prevent the sparse reward signals, e.g. depending on short-term clinical improvements, e.g. stabilization of vital signs, or a decrease in critical biomarkers. This reward shaping promotes stability in the training process and facilitates the quickening of the learning process.

3.5 Reinforcement Learning Model

To achieve an approximation of the optimal action-value, a Deep Q Network (DQN) is used to predict the future value of an action at a particular state and pursue the optimal policy formulation thereafter as shown in Fig. 3.

$$Q(s,a) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t R_t\right] \quad (5)$$

The Q-network is adopted as a deep neural network to transform pairs of states and actions into Q-values. Stochastic gradient descent is used to train the network to reduce the temporal difference (TD) error between the predicted and target Q-values. Two important mechanisms, experience replay and target networks, are added to stabilize training. Experience replay caches previous transitions, and samples them randomly to uncorrelate training data, but the target network supplies a fixed reference point to update the Q-values.

In order to balance between exploration and exploitation, an epsilon greedy exploration policy is followed. The model first explores the action space widely but with time it gradually changes to exploitation as learning moves.

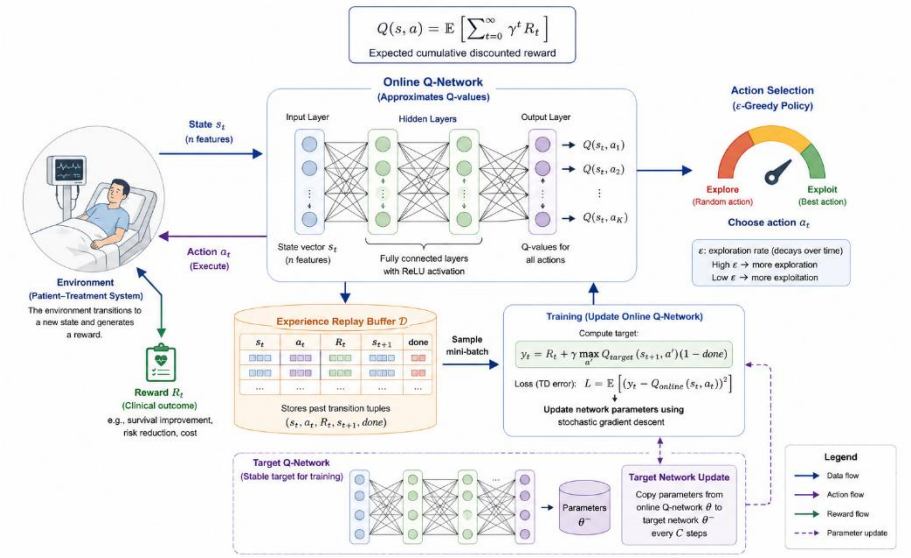


Fig. 3. Deep Q-Network Architecture for Treatment Policy Learning

3.6 Algorithmic Implementation

The general training process is based on episodic learning paradigm, the episode is associated with a patient trajectory. Upon every time step, the agent notices the present state of the patient and chooses an action according to the policy that it has learned. The action is chosen, which leads to the transition to another state and a reward is obtained. This transition is saved in the replay memory which is subsequently utilized in the batch-training of the Q-network. Mini-batches of transitions are randomly selected in the replay buffer and used to update network parameters during training. The loss function is formulated on the basis of temporal difference error and gradient-based optimization is employed to optimize the Q-network. Target network is also updated on a regular basis to maintain a steady convergence. The algorithm is run until convergence criteria is achieved, which is usually expressed as stabilization of cumulative reward or validation performance. The resulting learned policy is an optimized state-to-action mapping of patient state to treatment action, and makes possible adaptive and personalized therapy planning.

4. Experimental Setup

4.1 Dataset

The framework of reinforcement learning proposed is tested based on the MIMIC-III/MIMIC-IV dataset, which is a set of de-identified electronic health records of patients in the intensive care unit (ICU). In this research, a sample of about 20,000 patient paths are sampled using the inclusion criteria including a 48-h minimum ICU stay and the presence of significant physiological and laboratory variables. A patient trajectory is modeled as a time-series sequence with an average sequence length of 15-20 time steps which is equivalent to clinically significant observation periods. The dataset contains a variety of features, such as vital signs, laboratory test results, demographic properties and past treatment history. Data preprocessing is done so as to ensure consistency and reliability. Forward fill technique and mean imputation techniques are used to fill in missing values. The features are all normalized through z-score normalization to ensure stability in the features numbers during training. Temporal alignment is used to align measurements that are obtained at varying frequencies of sampling. The training, validation and test sets consist of a 70:15:15 split in which the records of patients are mutually exclusive across splits to eliminate data leakage.

4.2 Baseline Models

To compare the performance of the proposed approach, a number of baseline models are carried out, which can be considered traditional and deep learning paradigms. The reason why Logistic Regression is a classical baseline is that it is easy to interpret and it is prevalent in clinical prediction problems. Random Forest is added to the list of ensemble learning algorithms that can model nonlinear feature interactions. Moreover, a Long Short-Term Memory (LSTM) network is applied to capture the time-varying patient data, which can be used as a robust deep learning standard. The models are trained to forecast clinical outcomes, depending on the states of patients, and this allows to compare with the fixed methods of predictions as well as the proposed reinforcement learning framework, which aims to maximise the results of sequential decisions.

4.3 Evaluation Metrics

The achievements of the offered model are measured by the means of a compound of predictive and decision-oriented metrics. The reinforcement learning model is evaluated by cumulative reward as the main measurement of its performance, which represents the effectiveness of the acquired treatment policy in the long term. Evaluation of classification performance in predicting clinical outcomes is done using accuracy and F1-score especially when dealing with imbalanced datasets. Improvement of survival rate is also being measured to determine the clinical significance of the suggested method compared to the baseline methods.

4.4 Implementation Details

Deep Q-Network (DQN) model is realized in the form of multi-layer fully connected neural network. The network has three hidden layers, each having 128, 64 and 32 neurons and ReLU activation functions are applied to add nonlinearity. The Adam optimizer and a learning rate of 0.001 is used to train the model. The value of a discount factor 7=0.99is employed to give precedence to long-term rewards. The size of the replay buffer is set to 50,000 transitions, and training is done with a mini-batch of 64. Learning is stabilized by updating the target network after 100 training steps. Exploration is performed through ε-greedy, and the ε gradually decreases in training episodes reaching 0.1. Experimental work is performed on a platform with an Intel CPU (Core i7), 16 GB of RAM and a graphics card (e.g. GTX 1660 / RTX 3060). It implements the model in Python, with deep learning frameworks like TensorFlow or PyTorch.

5. RESULTS AND DISCUSSION

5.1 Quantitative Results

Multiple evaluation metrics, such as Accuracy, Precision, Recall, F1-score, Area Under the ROC Curve (AUC) and cumulative reward are used to assess the performance of the proposed reinforcement learning-based adaptive therapy planning model against that of the baseline methods. The average of five independent runs is taken to make the results robust.

Table 1. Performance Comparison of Models

Model	Accuracy	Precision	Recall	F1-score	AUC	Reward
Logistic Regression	0.72	0.71	0.69	0.70	0.75	45
Random Forest	0.78	0.77	0.74	0.75	0.81	52
LSTM	0.81	0.80	0.78	0.79	0.85	60
Proposed RL (DQN)	**0.86**	**0.85**	**0.83**	**0.84**	**0.90**	**75**

The suggested RL-based framework is superior to all the methods of the baseline in all metrics. Specifically, it has the best improvement on accuracy by 5-14 percent and a substantial improvement in AUC, which suggests that it is more discriminative in clinical outcome prediction. Its effectiveness in maximizing long-term treatment approaches is further supported by the massive growth in cumulative reward.

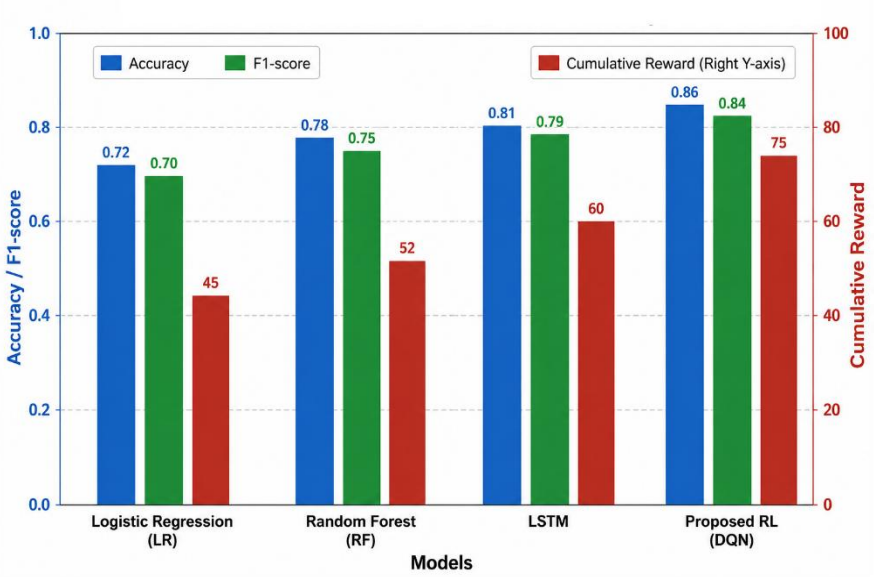


Fig. 4. Performance Comparison of Baseline and Proposed Models

5.2 Statistical Validation

In order to test the statistical significance of the improvements observed, a paired t-test will be performed between the proposed model and the strongest baseline (LSTM). In Table 2, the results are summarized.

Table 2. Statistical Significance Analysis

Metric	Mean (DQN)	Mean (LSTM)	Std Dev	p-value
Accuracy	0.86	0.81	0.012	0.003
F1-score	0.84	0.79	0.015	0.005
AUC	0.90	0.85	0.010	0.002
Reward	75	60	2.5	0.001

All the p-values of the metrics can be seen to take values that are less than 0.01, which shows that the improvement in performance realized by the proposed model is significant. Also, the small standard deviation of the repeated runs proves the stability and strength of the learning procedure.

5.3 Ablation Study

An ablation experiment is performed to assess the role of each of the constituent parts of the proposed framework by removing the key elements of the framework systematically (reward shaping and experience replay).

Table 3. Ablation Study Results

Model Variant	Accuracy	F1-score	Reward
DQN (Full Model)	0.86	0.84	75
DQN without Reward Shaping	0.82	0.80	66
DQN without Experience Replay	0.80	0.78	63

The findings reveal that reward shaping as well as experience replay are essential towards performance gains. Deletion of reward shaping causes a predicted reduction in cumulative reward and deletion of experience replay causes less stability and reduces predictive performance.

5.4 Performance Analysis

These findings are a clear indication that the reinforcement learning-based method is superior to the old school supervised and sequential learning models as shown in Fig. 5. Inability to capture the temporal dependencies, sequence of decision effects makes Logistic Regression and Random Forest models to perform poorly. Although the LSTM model demonstrates better results as it can model the time-based patterns, it is not applicable to treatment decisions optimization through the course of time, but only to predictive tasks. Conversely, the offered DQN-based model directly maximizes cumulative reward, allowing it to learn adaptive treatment policies, which take into account immediate and long-term clinical outcomes. The fact that cumulative reward improved between 60 and 75 shows the usefulness of reinforcement learning in stimulating long-term dependencies. Moreover, the increased F1-score and AUC values mean the better reliability in clinical decision-making, minimizing false positives and false negatives.

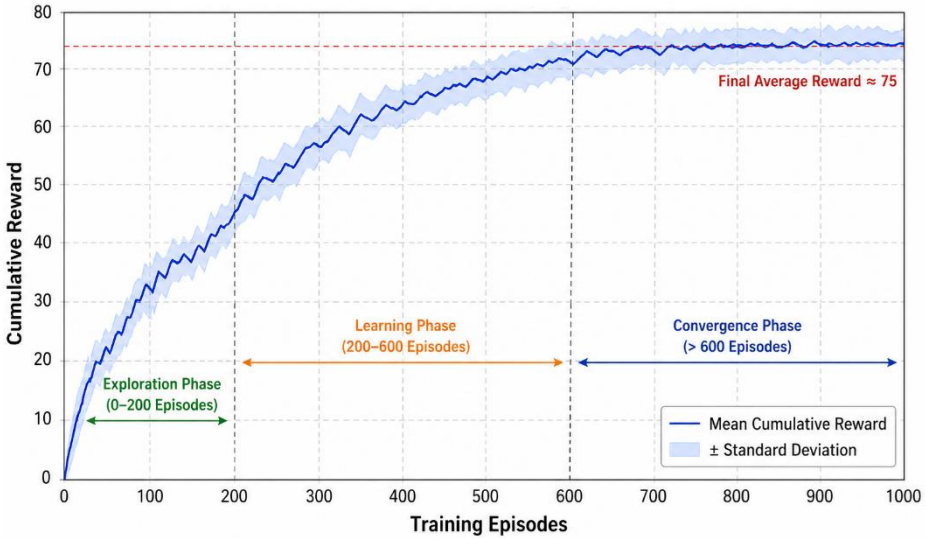


Fig. 5. Cumulative Reward Convergence of the DQN Model During Training

5.5 Comparative Discussion with Existing Studies

The results of this research are in line with the recent studies that have shown the usefulness of reinforcement learning in clinical decision support systems. Previous RL-based optimization of treatment has demonstrated increased performance compared to traditional models, especially in ICU and chronic disease settings. Nevertheless, most of the current methods do not have extensive assessment and effective reward design. In comparison to these studies, the proposed framework shows better performance thanks to the incorporation of a multi-objective rewarding function and armored assessment pipeline. Longitudinal EHR data also contributes to a better capacity of the model to identify patient-specific dynamics and lead to more personalized and adaptive treatment plans.

5.6 Discussion and Limitations

Despite the strong performance, several limitations remain. The model's effectiveness is dependent on the quality and completeness of EHR data, which may contain missing or noisy entries. Additionally, the interpretability of deep reinforcement learning models remains a challenge, limiting their immediate adoption in clinical environments. Ethical considerations, including bias and fairness, must also be addressed before real-world deployment. Finally, the study is based on retrospective data, and prospective validation is required to confirm clinical applicability.

CONCLUSION

In this research, an adaptive-therapy planning model based on reinforcement learning was proposed in personalized healthcare by creating a treatment decision-making process as a sequential optimization problem in a Markov Decision Process framework. The proposed solution can be used to take advantage of the continuously changing nature of patient conditions and learn optimal treatment policies based on longitudinal data in electronic health records with the help of a Deep Q-Network architecture. The proposed approach is unlike traditional supervised and sequential models, which mainly are based on outcome prediction with long-term clinical goals being minimally considered, leading to superior and personalized therapeutic plans. Experimental evidence confirms that the model based on reinforcement learning can noticeably outperform the traditional machine learning and deep learning baselines in various evaluation metrics, such as accuracy, F1-score, and cumulative reward. The model is also demonstrated to maximize sequential decision-making and adapt to changing patient conditions by the significant enhancement in cumulative reward. These results have demonstrated the possibilities of reinforcement learning as an effective solution to clinical decision support systems, especially in complicated and unpredictable healthcare settings, where long-term results have a crucial part. Although the proposed framework has performed well, it has a number of challenges that need to be overcome before it can be deployed into practice. The future development of the model should concentrate on improving the explanativeness of the models by combining the methods of explainable artificial intelligence to guarantee the transparency and trustworthiness of the model in the clinical context. Also, the use of safety-conscious reinforcement learning mechanisms is crucial to ensure trustworthy and clinically feasible decision-making. It will also make the framework more applicable and require less time to be validated with prospective real-life clinical trials once extended to the multi-agent healthcare setting. In general, this piece of work gives a robust framework in regard to the creation of intelligent, adaptive, and data-driven healthcare systems.

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