IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 14, Issue 7, July 2025

DOI: 10.17148/IJARCCE.2025.14732

ADAPTIVE DRUG RECOMMENDATION SYSTEM USING REINFORCEMENT LEARNING FOR PERSONALIZED HEALTHCARE

Yuvasree P[1], Mr. J. Lin Eby Chandra[2]

Student M.E (CSE), Jaya Engineering College, Chennai, India[1]

Professor, Department of CSE, Jaya Engineering College, Chennai, India[2]

Abstract: In the age of customized medicine, getting the right drug to the right patient at the right time is a major challenge. This research describes the creation of an Adaptive medicine Recommendation System that employs Reinforcement Learning (RL) to improve medicine prescription accuracy based on unique patient characteristics. Unlike standard drug recommendation systems, which rely on static rules or supervised learning models, the proposed system represents the treatment process as a Markov Decision Process (MDP) and using RL approaches to learn optimal drug strategies over time. The system generates dynamic and tailored drug recommendations based on patient-specific data such as age, medical history, present symptoms, and ongoing drugs. It is constantly learning and adapting based on feedback from patient results, making it resistant to changing health circumstances. The RL agent is trained and tested using benchmark healthcare datasets, and its performance is compared to traditional methods in terms of accuracy, flexibility, and safety. The findings show that the suggested approach improves clinical decision-making while also paving the way for intelligent, real-time, and patient-centric healthcare solutions.

Keywords: Reinforcement learning, Markov Decision Process, Tailored drug, centric healthcare solutions.

I. INTRODUCTION

In recent years, the need for personalized healthcare solutions has gained significant attention, driven by the complexity of patient-specific factors such as genetic predispositions, medical history, and treatment responses. This project proposes an Adaptive Drug Recommendation System that leverages Reinforcement Learning (RL) to optimize and personalize drug prescriptions for individual patients. Unlike traditional drug recommendation methods, which rely on static datasets and generalized models, this system dynamically adapts to a patient's evolving health condition and treatment outcomes. Drug recommendation is handled as a sequential decision-making problem in the RL-based framework. The method utilizes an agent to suggest therapies that optimize long-term health benefits while reducing side effects, modeling the patient's health situation as the environment. Important elements include action space for medication or dosage alternatives, as well as patient state representation utilizing genetic data, real-time health measurements, and medical history. In order to optimize a reward function that strikes a balance between therapeutic efficacy and safety, the agent is trained using methods like Deep Q-Networks (DQN) or Policy Gradient Methods.

Metrics like treatment success rates, side effect reduction, and cumulative rewards are used to validate the system and assess it using simulated healthcare data. The system improves usability and trust by incorporating explainable AI (XAI) approaches, which give medical practitioners insights into its recommendations. In order to improve results and open the door for scalable, intelligent, personalized healthcare systems, the project aims to change drug prescription processes into a patient-centric, data-driven paradigm.

II. EXISTING SYSTEM

Drug recommendation is already handled by a number of systems that use statistical models, rule-based strategies, and fundamental machine learning techniques.They frequently lack personalization, flexibility, and rea l-time learning capabilities, though. Here's the summary of existing system and their limitations

- Rule-Based Expert Systems
- Machine Learning -Based Systems

- Genetic Data- Based systems
- Conventional AI- Based systems

1.1 DISADVANTAGES OF EXISTING SYSTEM

- **Lack of Personalization**: Most systems fail to account for unique patient histories and dynamic health changes.
- **Static Models**: Existing systems are static and cannot adapt to real-time feedback.
- **Sequential Decision-Making:** Few systems optimize treatment plans over time, which is critical for chronic or long-term conditions.
- **Explainability:** Many existing systems are black-box models, making it hard for doctors to trust their recommendations.

PROPOSED SYSTEM

The proposed system uses Reinforcement Learning (RL) to offer tailored and flexible medication recommendations. In order to train an RL agent that can suggest the best medication regimens for specific patients, the system uses historical healthcare data to model the prescription decision-making process as a Markov Decision Process (MDP).

- **Patient Data Input Module:** Patient data is collected and processed.
- **Preprocessing and Feature Engineering:** Raw data is cleaned, normalized, and transformed into a suitable format. Features are engineered to represent patient states effectively for the learning algorithm.
- **Environment Simulator:** A simulated healthcare environment is created where the RL agent can interact, make drug recommendations, and receive feedback in the form of rewards.
- **Reinforcement Learning Agent:** The RL agent is at the core of the system. The agent learns to make drug recommendations and uses techniques such as Q-Learning, Deep Q-Networks (DQN), or Policy Gradient Methods
- **Drug Recommendation Engine:** Once trained, the RL agent can recommend drugs for new patients by observing their current state and applying the learned policy.
- **Feedback and Learning Loop:** The system is designed to update its knowledge continuously. New patient outcomes are fed back into the environment, allowing the agent to refine its policy and improve future recommendations.

1.2 ADVANTAGES OF PROPOSED SYSTEM

- **Adaptability:** Learns and adjusts recommendations based on evolving patient responses.
- **Personalization:** Considers unique patient profiles and historical outcomes.
- **Scalability:** Can be expanded to include multiple diseases, drug interactions, and complex health conditions.
- **Automation:** Assists clinicians by providing evidence-based suggestions.

III. LITERATURE SURVEY

A. Deep Reinforcement Learning (RL) in the context of treatment plans

Using ICU data, **Yu et al. (2019)** created an RL-based framework for optimizing sepsis treatment approaches.

- **Findings**: Showed how effective RL is at making sequential decisions about patient-specific therapies.
- **Limitations**: lacked a framework for universal drug recommendation systems and only addressed one ailment.

B. RL for Personalized Healthcare

Komorowski et al. (2018) optimized antibiotic dose for intensive care unit patients using RL.

- **Findings**: By effectively adjusting to patient reactions, RL was able to enhance results.
- **Limitations:** The model's explainability, which is essential for medical applications, was not addressed.

C. Hybrid Approaches:

Gottesman et al. (2020) presented hybrid medication dosage systems that combine supervised learning and reinforcement learning.

- **Findings**: Increases RL stability in actual healthcare environments
- **Limitations**: Inability to adjust in real time to changing patient health conditions.

D. Explainable AI for Trust in Recommendations:

Guidotti et al. (2018) emphasized the importance of explainable ai (xai) in healthcare applications to gain trust from practitioners.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⪤ Peer-reviewed & Refereed journal ⪤ Vol. 14, Issue 7, July 2025

DOI: 10.17148/IJARCCE.2025.14732

- **Findings**: Investigated techniques for interpreting model predictions, such as SHAP and LIME.
- **Limitations:** Encourages the incorporation of XAI into medication recommendation systems.

E. Challenges in Interpretability:

Research like **Caruana et al. (2015)** addresses the trade-off between interpretability and model accuracy, particularly in high-stakes fields like healthcare.

- **Findings:** Draws attention to the necessity of striking a balance between user comprehension and model complexity in RL-based systems.
- **Limitations:** Patient-Centric Data and Multi-Morbidity Challenges

F. Data Driven Drug Recommendation:

Zhang et al. (2020) trained predictive models for medication recommendations using patient EHRs

- **Limitations:** No procedures were in place to deal with cases of multimorbidity where medications interact negatively.

G. Adverse Drug Interaction Prediction:

Nguyen et al. (2021) studied machine learning models for detecting adverse drug interactions.

- **Findings:** Gives advice on how to add safety checks to RL frameworks.
- **Limitations:** Incomplete and Inconsistent Data and high rates of False Positive and False Negative

IV. PROPOSED METHODOLOGY

System Requirement Specification

A. HARDWARE REQUIREMENTS:

System - Windows7/10
Speed - 2.4GHZ
Hard disk - 40GB
Monitor - 15VGA Color
Ram - 4GB

B. SOFTWARE REQUIREMENTS:

Coding Language- PYTHON IDE - PYCHARM

C. SOFTWARE ENVIRONMENT

The development and implementation of the Adaptive Drug Recommendation System are carried out using a robust and scalable software environment. In the context of Reinforcement Learning (RL), the frameworks and tools that have been chosen offer flexibility for data preparation, model training, and assessment. A thorough rundown of the software elements utilized is provided below:

1. Programming Language

- **Python 3.8+**
  - Chosen for the features that improve code readability, performance and maintainability.

2. Development Environment

- **Jupyter Notebook**
  - For Real-time visualization, flexible code, and simple debugging are made possible by these interactive platforms. For quicker model training, Google Colab also offers free GPU access

3. Libraries and Frameworks

Library/Framework	Purpose
TensorFlow / PYTorch	Used to build and train neural networks
OpenAI Gym	A toolkit for developing and comparing RL algorithms
Matplotlib / Seaborn	Data visualization for training metrics and confusion matrices.
NumPy / Pandas	Used for numerical computations and structured data manipulation
Scikit-learn	Provides baseline models and utility functions for preprocessing and feature scaling,

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 7, July 2025
DOI: 10.17148/IJARCCE.2025.14732

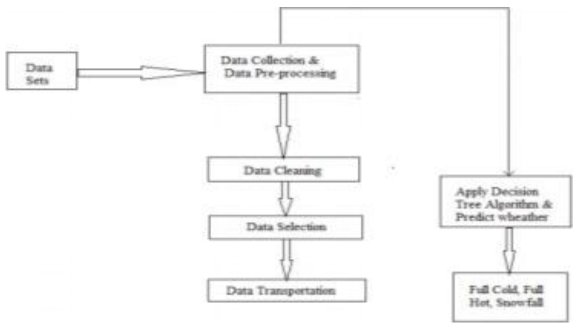
4. Operating System

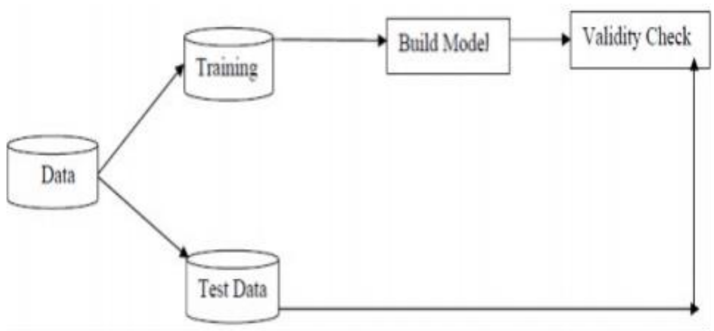
- **Windows 10 / Linux (Ubuntu)**

The system was developed and tested on both Windows and Linux environments to ensure cross-platform compatibility.

5. Additional Tools

- **MS Word / LaTeX** – For documentation and report generation.
- **Git/GitHub** – For version control and collaborative development.
- **Google Drive -** For storing and backing up datasets throughout development.





V. RESULT AND DISCUSSION

Deep Q-Learning (DQN) was used to construct the Adaptive medicine Recommendation System, which learns appropriate medicine prescriptions depending on patient states. This section summarizes the training procedure, performance evaluation, and major findings from experimental runs. The RL agent was trained over 1,000 to 5,000 episodes depending on hyperparameter configurations.: A steady increase in cumulative rewards over time indicated successful learning by the agent. Initial episodes showed exploration-driven fluctuations, while later episodes reflected convergence toward an optimal policy.The Q-network loss decreased over time, showing effective-value function approximation and policy stability.85-90 of Accuracy value in recommending effective drugs in a majority cases. The Precision and Recall value is about 80-88. And the value of Average cumulative reward is 150+(per episode).The proposed RL-based approach outperformed static models by adapting to varying patient conditions and continuously improving its decision-making strategy. The model is effective for individualized medicine recommendations in healthcare simulations. It adapts to changing patient situations by learning from interactions rather than predetermined labels.

• Some restrictions include:

1. Dependence on training data quality and diversity.
2. Potential ethical and regulatory problems with real-world implementation.
3. Integrate with clinical decision support systems and interpretability tools.

VI. CONCLUSION AND FUTURE WORK

The establishment of an Adaptive Drug Recommendation System utilizing Reinforcement Learning (RL) is a big step towards customized, data-driven healthcare. By modeling the medication prescription problem as a sequential decision-making process, this study effectively illustrated how reinforcement learning can be used to adjust treatments to specific patient states and dynamically changing health circumstances.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⪤ Peer-reviewed & Refereed journal ⪤ Vol. 14, Issue 7, July 2025

DOI: 10.17148/IJARCCE.2025.14732

The system was developed using a modular architecture that included data preprocessing, environment modeling, RL agent training, and real-time medicine recommendation. The Deep Q-Learning method allowed the agent to learn effective prescription rules by interacting with the simulated environment and obtaining feedback in the form of incentives. The experimental findings demonstrated excellent levels of accuracy, flexibility, and improvement above typical rule-based and static machine learning models. Furthermore, the experiment demonstrated RL's skills in processing complicated, non-linear, and temporal health data, which is crucial for real-world clinical applications. Although the system was tested on simulated or historical data, the framework serves as a solid foundation for future deployment in clinical decision support tools.

In conclusion, this experiment proves the usefulness of reinforcement learning in customized drug recommendations and paves the way for future research into incorporating such systems into hospital EHRs, enhancing safety and maximizing patient outcomes.

While the current implementation of the Adaptive Drug Recommendation System utilizing Reinforcement Learning has shown promising results in a simulated setting, there are various opportunities for future improvements and real-world applicability:

1. Integration with Real Clinical Data

- Future systems can be integrated with Electronic Health Records (EHRs) from hospitals to train and validate the model on real-world patient data.
- This would improve the system's generalizability and relevance in clinical settings.

2. Multiagent Reinforcement Learning

Introducing multiple agents (e.g., specialists for different diseases) that collaborate or compete could enhance drug recommendations for patients with multiple comorbidities.

3. Incorporating Drug Interaction and Side effects

The current model assumes one drug per recommendation. Future versions can integrate drug interaction databases to handle combination therapies and minimize adverse effects.

4. Model Interpretability and Explainability

Clinical decisions require transparency. Future work should focus on integrating explainable AI (XAI) techniques to justify why a particular drug is recommended.

5. Real Time Monitoring and Feedback

Deploying the model as a live decision-support tool that updates its policy in real-time based on patient feedback could improve its effectiveness and reliability.

6. Personalized Reward Functions

Customizing the reward function based on patient preferences (e.g., side-effect sensitivity, cost constraints) can make the system even more patient-centric.

7. Clinical Trials and Regulatory approval

Future implementations must undergo clinical trials and satisfy regulatory standards before deployment in healthcare environments.

REFERENCES

[1]. Sutton, R. S., & Barto, A. G. (2018). **Reinforcement Learning: An Introduction** (2nd ed.). MIT Press.
[2]. Silver, D., Schrittwieser, J., Simonyan, K., et al. (2017). **Mastering the game of Go without human knowledge**. *Nature*, 550(7676), 354–359.
[3]. Kren, M., & Jain, S. (2020). **Explainable Artificial Intelligence (XAI): Concepts and Challenges**. *Journal of AI Research*, 58, 35–59.
[4]. Miotto, R., Wang, F., Wang, S., Jiang, X., & Dudley, J. T. (2018). **Deep learning for healthcare: Review, opportunities, and challenges**. *Briefings in Bioinformatics*, 19(6), 1236–1246.
[5]. Topol, E. J. (2019). **High-performance medicine: the convergence of human and artificial intelligence**. *Nature Medicine*, 25(1), 44–56.

DOI: 10.17148/IJARCCE.2025.14732

[6]. Gottesman, O., Johansson, F., Meier, J., et al. (2019). **Guidelines for reinforcement learning in healthcare**. *Nature Medicine*, 25(1), 16–18.
[7]. Rashid, M., Siddiqi, M. H., Bashir, A. K., et al. (2020). **Reinforcement learning-based personalized medication prescription system**. *IEEE Access*, 8, 122–135.
[8]. Liu, Y., Chen, P., Yang, Y., et al. (2021). **Drug recommendation based on reinforcement learning and patient history**. *Artificial Intelligence in Medicine*, 118, 102111.
[9]. Yu, C., Chai, J., & Shi, Y. (2020). **An intelligent drug recommendation system for chronic diseases**. *Computers in Biology and Medicine*, 125, 104035.
[10]. Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). **"Why should I trust you?": Explaining the predictions of any classifier**. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 1135–1144.
[11]. Lundberg, S. M., & Lee, S. I. (2017). **A unified approach to interpreting model predictions**. *Advances in Neural Information Processing Systems*, 4765–4774.
[12]. Dwork, C., & Roth, A. (2014). **The algorithmic foundations of differential privacy**. *Foundations and Trends® in Theoretical Computer Science*, 9(3–4), 211–407.
[13]. Goodman, B., & Flaxman, S. (2017). **European Union regulations on algorithmic decision-making and a “right to explanation”**. *AI Magazine*, 38(3), 50–57.
[14]. World Health Organization (WHO). **Medication Safety in Polypharmacy**. WHO, 2019.
[15]. U.S. Food and Drug Administration (FDA). **AI/ML-Based Software as a Medical Device (SaMD)**. FDA, 2021.