IMPROVE YOUR GAIT WITH LABORATORY AGENT

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INTRODUCTION

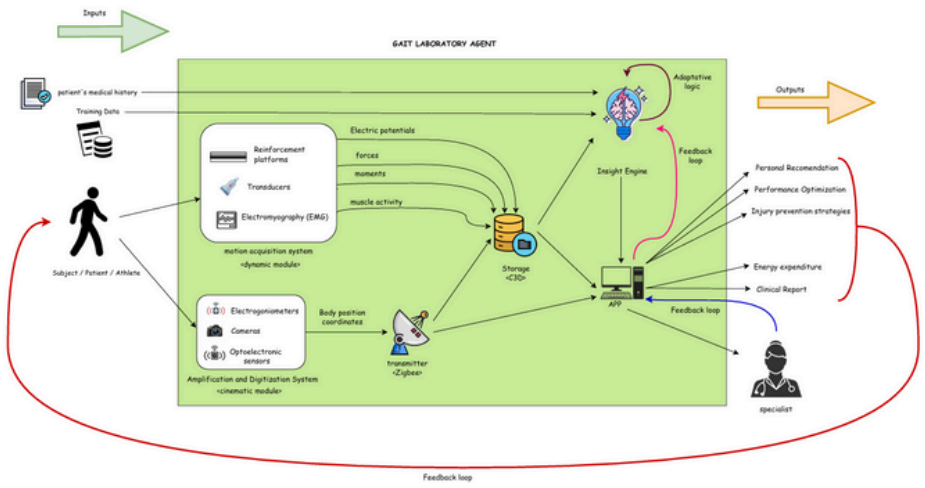
Gait analysis is essential in identifying movement disorders and enhancing physical performance. Traditional gait labs, while effective, are often inaccessible due to their complexity and cost. Existing solutions rely heavily on manual evaluation and lack real-time, adaptive feedback. The challenge lies in developing an intelligent, automated system that captures and analyzes gait data, learns from it, and generates personalized recommendations to improve health outcomes.

GOAL

This work aims to answer the question:
How can a Gait Laboratory Agent provide personalized gait improvement recommendations?
Develop an intelligent system that combines simulation, biomechanical models, and reinforcement learning to generate individualized suggestions based on patient data.

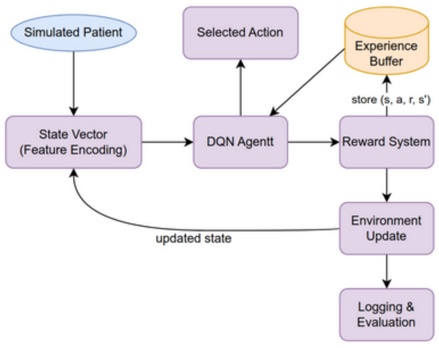
PROPOSED SOLUTION

The proposed solution was designed using systems science principles—including system dynamics, cybernetics, and systems thinking—to model the gait lab as a complex adaptive system. This perspective enabled the identification of feedback loops, nonlinear dependencies, and key variables that affect rehabilitation. Based on this, we implemented a closed-loop architecture where a reinforcement learning agent interacts with virtual patients in a simulated environment. The design supports adaptive decision-making and personalized recommendations through continuous feedback.



EXPERIMENTS

To validate the proposed solution, we developed a custom simulation environment using Gymnasium. A Deep Q-Learning (DQN) agent was trained for 50,000 timesteps using synthetically generated patient data. Each patient was represented by a structured state vector containing clinical and biomechanical features such as joint mobility, balance, and muscle strength. The simulation also incorporated a Degrees of Freedom (DOF) gait model to reflect a wider range of physical conditions and promote agent generalization. After training, the agent was evaluated on a hold-out test set comprising 20% of the data

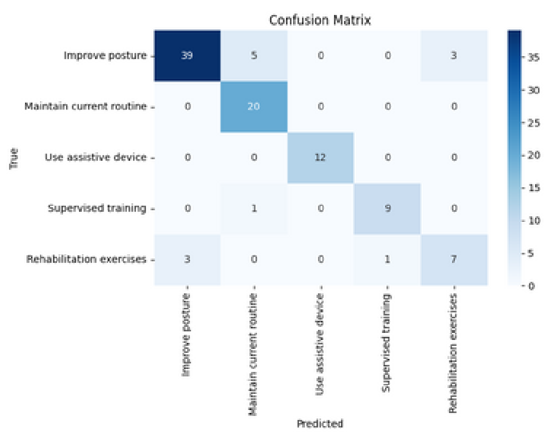


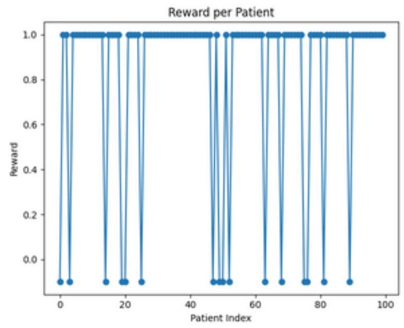
RESULTS

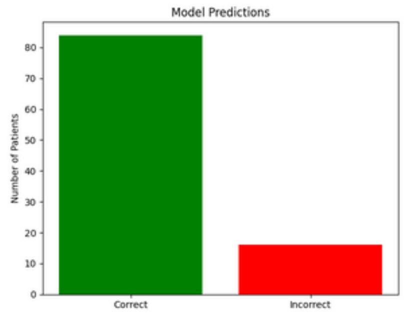
The agent achieved strong performance across standard classification metrics:

Metric	Score
Accuracy	87%
Precision (weighted)	88%
Recall (weighted)	87%
F1 Score (weighted)	88%

The confusion matrix revealed high agreement between predicted and actual recommendations. Additional charts showed the number of correct vs. incorrect predictions and stable reward accumulation across episodes, confirming consistent learning behavior. While the approach demonstrated promising generalization, performance on borderline or noisy cases could be further improved in future iterations.







CONCLUSIONS

In conclusion, by developing a system that combines biomechanical simulation, systemic thinking, and deep reinforcement learning. The agent analyzes clinical and simulated movement information, represented by a multi-DOF model, to generate personalized actions in the form of rehabilitation recommendations. Thanks to training with consistent data and structured feedback through rewards, the agent learned to select appropriate interventions for each patient.

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