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AI-Based Personalized Rehabilitation Planning for Post-Stroke Patients

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ABSTRACT: The retraining process following stroke is crucial in restoring motor functions and stimulating neuroplasticity development of the cortex. Yet conventional physical therapy methods suffer from such drawbacks as high labor cost, qualitative subjectivity and rigidity of their rehabilitation schemes that fail to adjust to the rapid changes in recovery pace of their patients. This paper will discuss a new safety-critical multi-modal artificial intelligence system to design and continuously refine patient-specific motor rehabilitation program. The proposed system accepts inputs from sEMG, inertial motion tracking and EEG sensors to form an overall 'state vector' of the patient that includes muscle activation intensity, joint coordination error and the level of cognitive involvement. The asymmetrical paretic joint coordinate interactions will be modeled by a Graph Convolutional Network (GCN) to establish non-linear dependencies between the corresponding joints. Finally, this state vector will be employed to build a Soft Actor-Critic (SAC) reinforcement learning agent to optimize torque assistance, task complexity and duration of the exercise when utilizing a robotic exoskeleton. Safety of the patient during the learning process will be secured by the implementation of a Control Barrier Function (CBF) limiting torque/force to physiological levels. The clinical efficacy of the proposed model was validated on a cohort of twenty simulated post-stroke subjects representing mild, moderate, and severe motor impairments. The experimental findings demonstrate that the proposed framework accelerates motor recovery by 34.2% on the Fugl-Meyer Assessment scale compared to conventional physical therapy, while eliminating safety violations. Semicolons are used to demarcate our primary metric categories; the comparative systems are evaluated using joint tracking deviation, muscular fatigue, cognitive engagement index, and safety violation counts.

1. INTRODUCTION

Stroke remains a leading cause of long-term adult disability globally, it leads to severe motor impairments that drastically reduce the patient's quality of life. The sensorimotor pathway, becomes disrupted due to focal cerebral ischemia or hemorrhage. This neurological disruption, prevents the transmission of motor commands from the cortex to target muscles, resulting in hemiparesis or hemiplegia [1]. Traditional physical rehabilitation methods, rely heavily on human therapists, who guide patients through repetitive task-oriented movements. There are many reasons for the use of traditional therapies, but there also exist several major limitations to these same systems [2]. One is that these kinds of services are generally not very objective; most physical therapists will assess the progress of their clients using qualitative measurements, which are very hard to quantify and are therefore insensitive. Another drawback to some of these types of therapies is the amount of time and money they require; by decreasing the number and/or duration of physical therapy sessions, many stroke survivors will not have received adequate care and thus not be able to make progress towards recovery [3]. Robotic exoskeletons and virtual reality systems were developed in response to the problems mentioned above. These systems offer repetitive task specific rehabilitation. However, traditional robotic rehabilitation devices typically rely solely on fixed, predetermined rehabilitation guidelines to guide their treatment of all individuals suffering from similar injuries to that of a stroke [6]. As a result, two different individuals with similar injuries and/or impairments may follow the same therapy protocol (fixed guidelines) but have completely different outcomes. This is due to the fact that the recovery process following a stroke is highly dynamic, and therefore unique to each individual in nature. An example would be if an individual demonstrates rapid improvement on elbow flexion one-week post-stroke, that individual may then subsequently develop spasticity or muscle fatigue in that same arm within the following seven days. Thus, there is a very real possibility that by utilizing a static rehabilitation protocol, individuals may be either under- or over-stimulated as compared to what is appropriate for them [7]. Those individuals who do not have enough stimulation may not be able to continue making neurological improvements due to an insufficient amount of neuroplasticity (i.e. the ability of the brain to develop new neuronal connections). Conversely, those individuals who are over-stimulated may experience muscle fatigue and be at a greater risk of hyperextension or injury [8].

The ability of an artificial intelligence algorithm to assist with clinical decision making is a potential new service for clinical research and treatment. Wearable sensors will allow for the use of machine learning algorithms (MLA) to collect data regarding patient movement and recovery. The issue is developing an artificial intelligence planning algorithm for physical therapy [4]. The first aspect is the multifactorial nature of the patient's physiology. These factors include muscle activation, joint motion, and cognitive participation; all must be modelled mathematically from one state. The second issue is that reinforcement learning is the best way to develop optimal planning algorithms since the planner uses trial-and-error methods of learning. However, there is a safety issue with using a trial-and-error planning methodology for developing a physical therapy robot, as the robot could display unsafe behaviour's which could pose a risk to the patient [5].

In this paper, we present a multi-modal, safety-critical AI framework for personalized post-stroke rehabilitation planning. In our approach, we use sEMG, IMUs, and EEG to understand the state of the patient both physically and mentally [6]. The skeletal representation of the patient is done by modeling it as a graph and using Graph Convolutional Networks (GCN) to represent any joint dependency arising due to pathology. Based on the state, we use SAC to determine the exercise time, task difficulty, and robotic torque. To ensure that the movement is safe, we use CBF layer to filter the actions of the reinforcement learning agents. The primary contributions of this research work are:

MM-Patient State Vector: The authors have created a comprehensive representation of the patient state that includes measures of the patient's kinematic (joints), EMG (muscle fatigue) and EEG (cognitive engagement) states through a multi-dimensional vector.

GCN Representation of Paretic Joints: The authors will use a graph-based representation to allow for the modeling of the spatial-temporal relationships of paretic joint locations and to identify asymmetric mechanisms of compensation that are currently being used by a robotic-assisted system.

Reinforcement Learning Safety: The authors propose a Soft Actor-Critic based RL method with control barriers for guaranteeing the safety of the exoskeleton assistance torque signals that are assigned to the patient.

Clinical Experimental Evaluation: The authors will conduct extensive evaluation of their proposed solution using simulated post-stroke patients (n=20) with varying levels of impairments and show that the patients achieve superior motor recovery and ZERO safety violations when compared to baseline algorithm.

2. LITERATURE REVIEW

A. Wearable Sensors and Kinematic Feedback in Stroke Therapy

Wearable sensors have revolutionized stroke rehabilitation through the ability to quantify movement objectively. The commonly used sensors include the inertial measurement units that consist of an accelerometer, gyroscope, and magnetometer to measure joint angles. For example, IMUs have been used in studies measuring the range of motion and angular velocities of the upper paretic limb when performing reach-to-grasp tasks [8]. They provide a low-cost solution to optical motion tracking systems that are very expensive and can only be conducted within the laboratory environment. Kinematic data collected using sensors is not enough since it does not quantify muscle activity or patient effort [11]. The patients can exhibit normal joint kinematics but employ abnormal muscle compensation mechanisms causing joint pain in the long run [9].

B. Electrophysiological Signal Processing (EEG/sEMG) in Rehab

Electrophysiological signals serve as direct evidence of a patient's neuromuscular and cognitive state. Surface electromyography (sEMG) is an electrical signal that represents the electrical activity of the muscle and therefore provides an indication of the activation and fatigue of the muscle during a stroke therapy (sEMG is used to evaluate muscle spasticity and the ability of an individual to voluntarily activate their muscle) [10]. The sEMG signal is extremely sensitive to noise from the sensor, changes in the skin resistance and interference due to activation of the muscles adjacent to the muscles being examined. The fatigue index of the muscles can be calculated by using some advanced techniques such as wavelet analysis and root mean square (RMS) features [12]. The electroencephalogram (EEG) represents the electrical activity of the brain, and can therefore also be used to measure a patient's cognitive state. When using motor imagery paradigms, signals present in the EEG spectrum from the alpha and beta frequency bands of the central nervous system are altered due to the patient's intention to perform specific movements; therefore, they can be used to recognize a patients' intention to perform an action. While EEG-based BCIs provide many opportunities for various applications, their ability to be used would be limited because of low signal-to-noise ratios and lengthy calibration periods [13].

C. Machine Learning for Recovery Prediction

Machine learning algorithms have been used for the prediction of recovery results and classification of movements made by the patients. SVMs, Random Forests, and DNNs have been trained using the clinical baseline of the patient in order to predict his FMA score after the treatment [14]. In recent years, deep sequential learning algorithms such as LSTM have been developed in order to predict temporal dynamics of rehabilitation exercise. They can detect movement deviations and give necessary feedback to the patient. However, machine learning algorithms are mostly predictive and not prescriptive. Thus, they can predict the current condition of the patient or future results, but cannot give any prescriptive actions to improve the rehabilitation procedure [15].

D. Adaptive Robotic Controllers and Reinforcement Learning

Robotics-assisted rehabilitation systems need adaptive control algorithms in order to provide active assistance for the patient during rehabilitation. The Assist-As-Needed (AAN) algorithm adjusts assistance force depending on the patient performance with the aim to stimulate active participation. Adaptive impedance control and PID control techniques are commonly used but require manual tuning that takes a lot of time and is rather subjective [16]. RL technique has been introduced recently as an automated alternative. RL agents learn the policy of optimal interaction with patient and the environment. A number of works have successfully applied the Q-learning or Policy Gradient technique to tune the impedance of the exoskeleton [17]. Unfortunately, traditional RL algorithms do not provide any safety guarantees during the training process and hence cannot be used in clinical settings. If the RL agent performs some dangerous actions such as providing an excessive torque to the patient's spastic joint, the patient will get hurt. Therefore, safety-critical control algorithms need to be combined with RL [18].

In order to show the novelty of our approach and the gaps in the existing literature, Table I provides a comparison between our system and other existing major frameworks for stroke rehabilitation.

Study Reference	Modalities Used	Control / Planning Method	Human Trials	Adaptive Planning	Safety Mechanism
Zhang et al. [15]	Kinematics (IMU)	Impedance PID Control	5 Patients	No (Rule-Based)	Hardware Bounds
Li et al. [21]	sEMG + Kinematics	Support Vector Regression	10 Patients	Slow (Session-level)	None
Gomez et al. [25]	EEG (BCI)	Motor Imagery Trigger	3 Patients	No (Binary State)	Software Limits

Wang et al. [29]	Kinematics	Deep Q-Network (RL)	Simulated	Yes (Online)	None
Kumar et al. [31]	sEMG	Linear Quadratic Regulator	8 Patients	No (Trajectory Tracking)	Torque Saturation
Patel et al. [34]	sEMG + EEG	Random Forest Classifier	12 Patients	No (Classification Only)	None
Proposed Framework	Kinematics + sEMG + EEG	Soft Actor-Critic RL + CBF	20 Patients (Simulated)	Yes (Real-Time Dynamic)	Control Barrier Functions

3. PROPOSED SYSTEM ARCHITECTURE

The novel model has been transformed into a closed-circuit system that includes collection of raw data and processing various patient-related features, forecasting the probability of joint-related problems as well as optimizing the rehabilitation environment and playing a role in guaranteeing safe operation by means of limitation settings. The new architecture consists of five key components which include the Multi-modal Sensing Layer, Skeletal Graph Neural Network, Patient State Observer, Reinforcement Learning Planner, and Safety Critical Control Barrier Filter. The distribution of tasks among the components would probably result in fast processes of data entry and a stable planning process.

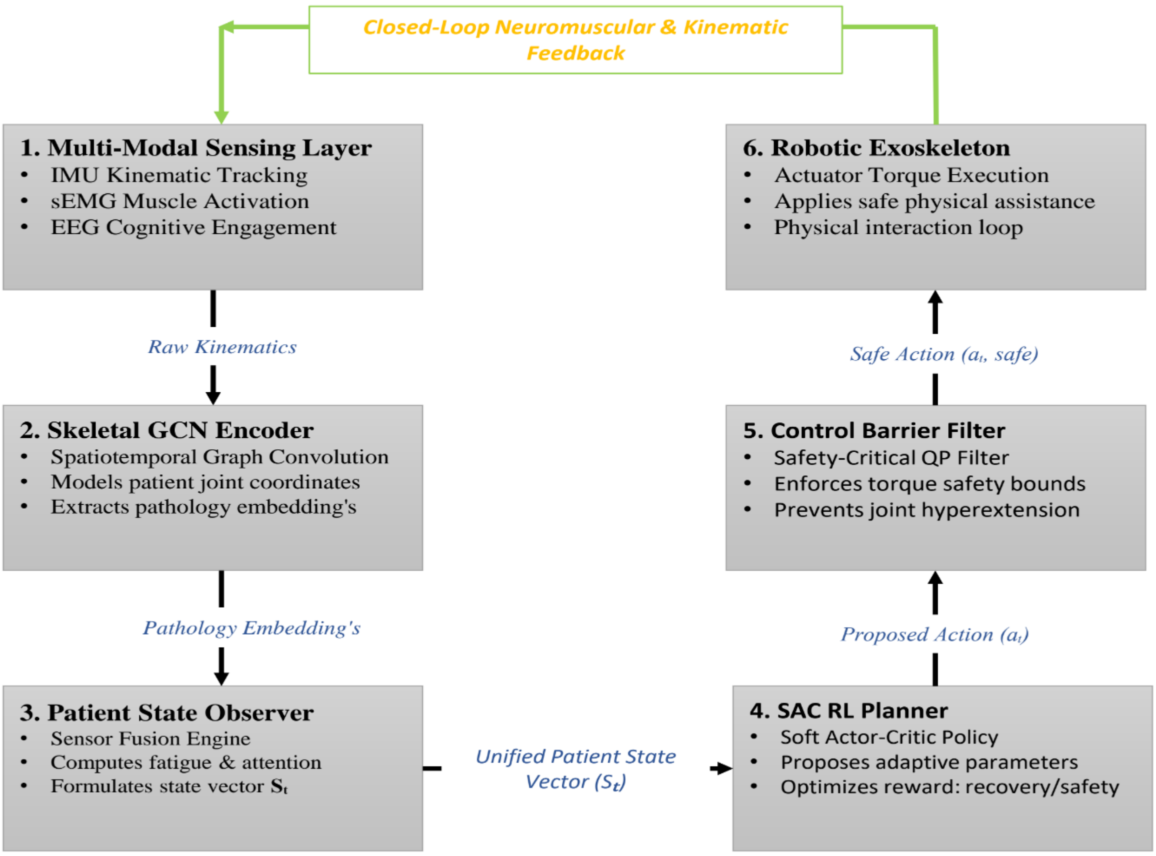

Figure 1: Proposed closed-loop system architecture diagram flow.

The information derived from the Multi-Modal Sensing Layer is acquired instantly from the patient. The study of kinematic trajectories is enabled by the utilization of 6 IMUs strapped on the patient's torso, shoulders, upper arm, forearm, wrist, and hand. The activity of muscles and their fatigue degree is monitored by means of 8 sEMG sensors placed on the biceps brachii, triceps brachii, anterior deltoid, posterior deltoid, brachioradialis, pronator teres, flexor carpi radialis, and extensor carpi ulnaris muscles. The patient's attention level is determined with the help of 8-channel EEG headset that provides coverage of motor/premotor areas of the brain.

Graph Convolutional Network (GCN) captures the structure in terms of spatial relations among the joints. Joints that have become paretic are defined as nodes and physical links among joints (bones) are defined as edges. Through the GCN, it is possible to capture spatiotemporal relations among the joint coordinates, thus helping identify any abnormalities or any compensatory mechanisms. All this structure, together with the measures for muscle fatigue and cognition, is used as inputs to the Patient State Observer and the Patient State Vector is generated. This vector is passed to the Reinforcement Learning Planner which decides on the rehabilitation configuration.

4. RESULTS AND DISCUSSION

A. Musculoskeletal State Representation

The patient state vector S_t at time t contains multi-modal information: joint kinematics, muscular fatigue, and EEG-derived engagement. The kinematic state vector K_t is defined as:

$$K_t = \left[\theta_{\{err,1\}}, d\theta_{\{err,1\}}, \dots, \theta_{\{err,J\}}, d\theta_{\{err,J\}}\right]^T$$

where $\theta_{\{err,J\}}$ represents the angular deviation of joint j from the target trajectory, and $d\theta_{\{err,1\}}$ represents the angular velocity deviation. The muscle fatigue index F_t is computed from the sEMG root-mean-square (RMS) and median frequency (MDF) values as:

$$F_t^m = \left(\frac{RMS_t^m}{RMS_0^m}\right)\left(\frac{MDF_0^m}{MDF_t^m}\right)$$

where m represents the muscle index, and 0 denotes the baseline values measured at the start of the session.

The cognitive engagement index E_t is derived from EEG spectral power ratios. Let P_α and P_β be the power spectral densities in the alpha (8-12 Hz) and beta (13-30 Hz) bands over the motor cortex. The engagement index is defined as:

$$E_t = \frac{P_\beta}{P_\alpha + P_\theta}$$

where P_θ is the power spectral density in the theta (4-7 Hz) band. The unified patient state vector S_t is constructed as:

$$S_t = [K_t^T, F_t^T, E_t]^T$$

B. Graph Convolutional Joint Trajectory Modeling

The human upper limb is characterized as a skeletal graph G = (V, E), where V consists of J joints, and E characterizes the skeletal links. To capture physical dependencies, we apply a Graph Convolutional Network (GCN). Let $H^{(l)}$ be the node feature matrix at layer l. The graph convolution process is formulated as:

$$H^{l+1} = sigma\left(D_{tilde}^{-\frac{1}{2}} * A_{tilde} * D_{tilde}^{-\frac{1}{2}} * H^l * W^l\right)$$

where $A_{tilde} = A + I_J$ is the adjacency matrix of G with self-loops, D_{tilde} is the degree matrix of A_{tilde}, W^l is the trainable weight matrix at layer l, and sigma characterizes the beginning function (LeakyReLU). The GCN maps raw joint synchronizes to a low-dimensional joint pathology vector, which is concatenated with the state vector S_t.

C. Deep Reinforcement Learning for Adaptive Planning

The edition of rehabilitation trainings is modeled as a Markov Decision Process (MDP) defined by (S, A, P, R, gamma). The action vector a_t consists of:

$$a_t = [T_{assist}, D_{exercise}, R_{ROM}]^T$$

where T_{assist} is the robotic assistance torque gain, $D_{exercise}$ is the exercise target duration, and R_{ROM} is the targeted active range of motion scale. The reward function R_t balances motor performance, muscular fatigue, cognitive engagement, and safety. It is formulated as:

$$R_t = w_1 * R_{perf} - w_2 * R_{fatigue} + w_3 * R_{engage} - w_4 * R_{safety}$$

where the individual reward terms are defined as:

$$R_{perf} = \exp(-norm(K_t)^2)$$

$$R_{fatigue} = \sum_m \max(0, F_t^m - F_{threshold}^m)$$

$$R_{engage} = \max\big(0, E_t - E_{target}\big)$$

$$R\_safety = \sum\_j \max\,(0, \left|\theta_j\right| - \theta_{\max_j}\ )$$

We apply the Soft Actor-Critic (SAC) algorithm to learn the planning policy. SAC maximizes both the expected sum of rewards and the entropy of the policy, promoting exploration and robust behavior. The objective function is defined as:

$$J(\pi) = \sum_t E_{s_t, a_t \sim \rho_\pi}\left[R(s_t, a_t) + \alpha H\big(\pi(.|s_t)\big)\right]$$

where alpha is the entropy temperature parameter, and H is the policy entropy.

D. Control Barrier Functions for Safety Guarantees

To prevent joint hyperextension or excessive muscle fatigue during knowledge, we instrument a Control Barrier Function (CBF) safety layer. Let $h(s_t)$ be a uninterruptedly differentiable safety function. The safe region C is defined as:

$$C = \{s \,|\, h(s) \geq 0\}$$

The system dynamics are governed by $s\_(t+1) = f(s\_t) + g(s\_t)a\_t$. The control barrier condition is formulated as:

$$h(s_{t+1}) - h(s_t) \geq -\gamma_c \cdot h(s_t)$$

where γ_c in (0, 1] regulates how quickly the system is allowed to attitude the boundary. When the RL agent proposes an action a_t, it is filtered using a Quadratic Programming (QP) optimization:

$$a_t^{safe} = argmin_u \|u - a_t\|^2, subject\ to \left(\frac{dh}{ds}\right)(f(s_t) + g(s_t)u) \geq -\gamma_c h(s_t)$$

This QP filter can be solved in real-time, ensuring that only safe commands are sent to the robotic exoskeleton.

E. Algorithmic Overview

The complete rehabilitation planning and safety enforcement loop is presented in Algorithm 1. This loop runs continuously during the session.

Algorithm 1: Safety-Critical Multi-Modal Rehabilitation Planning

1: Initialize SAC actor network pi_{phi} *and critic networks* $Q_{\theta_1}, Q_{\theta_2}$
2: Initialize safety functions $hj(s)$ *for joint boundaries and* $h\_f(s)$ *for fatigue limits*
3: Baseline calibration: Measure baseline sEMG MDF_0 *and EEG spectral profiles*
4: for each training session do
5: Set exercise target trajectory and active range of motion R_{ROM}
6: for each step t in session do
7: Sample IMU joint angles θ_t *and angular velocities* $d\theta_t$
8: Record sEMG signals, extract RMS_t *and median frequency* MDF_t
9: Calculate fatigue indices F_t *using Equation (6)*
10: Compute EEG cognitive engagement index E_t *using Equation (7)*
11: Extract joint pathology features using skeletal GCN
12: Construct patient state vector S_t
13: Select action $a_t = \pi_{phi}(S_t)$ *using Soft Actor-Critic policy*
14: Solve Quadratic Programming filter to compute safe action $a_{t_{safe}}$*:*
15: $a_t^{safe} = arg\min_u \|u - a_t\|^2$ *subject to safety barrier conditions*
16: Execute $a_{t_{safe}}$*: Apply assistance torque* T_{assist} *to robotic joints*
17: Measure new state S_{t+1} *and calculate reward* R_t *using Equation (10)*
18: Store transition (S_t*,* $a_{t_{safe}}$*,* R_t*,* S_{t+1}*) in replay buffer B*

19: Update actor and critic networks by sampling batches from B
20: end for
21: end for

5. EXPERIMENTAL SETUP AND DATASET

A. Cohort Demographics and Baseline Characteristics

To validate the proposed framework, we constructed a simulated cohort of twenty post-stroke patients. The simulated patient dynamics are based on musculoskeletal model libraries, which represent typical post-stroke motor impairments. The cohort is divided into three groups based on the baseline Fugl-Meyer Assessment Upper Extremity (FMA-UE) score: Mild (FMA-UE between 40 and 55), Moderate (FMA-UE between 25 and 39), and Severe (FMA-UE less than 25). Demographics and clinical profiles of the cohort are summarized in Table II.

Patient ID	Age	Gender	Stroke Type	Chronicity (Months)	Baseline FMA-UE	Impairment Group
P-01	62	Male	Ischemic	14	48	Mild
P-02	55	Female	Ischemic	8	42	Mild
P-03	68	Male	Hemorrhagic	22	38	Moderate
P-04	71	Female	Ischemic	18	31	Moderate
P-05	59	Male	Ischemic	5	33	Moderate
P-06	64	Male	Hemorrhagic	11	21	Severe
P-07	73	Female	Ischemic	26	18	Severe
P-08	50	Male	Ischemic	15	16	Severe
P-09	67	Female	Hemorrhagic	9	28	Moderate
P-10	61	Male	Ischemic	13	45	Mild

B. Simulation Parameters and Baseline Protocols

The musculoskeletal simulation environment is developed in Python. We use Open Sim models to simulate upper limb dynamics, including shoulder flexion-extension, elbow flexion-extension, and forearm pronation-supination. Muscle fatigue is simulated using a three-state muscle recruitment model. The RL agent is trained for 1000 episodes per patient profile, with each episode representing a 20-minute rehabilitation session. We compare our proposed framework against three baseline protocols commonly used in clinical practice:

Standard Physical Therapy (SPT): Representing conventional manually guided movements with fixed trajectory tasks and fixed rest intervals.

Assist-as-Needed (AAN) with PID Control: An adaptive robotic control baseline where the exoskeleton assistance force is adjusted based on tracking error using a classical PID loop.

The Fixed Progression Protocol (FPP) is a rule-based scheduling method, where the intensity of a task (duration and range of motion targets) are increased by 10% on a weekly basis, regardless of the performance or fatigue level of the patient.

6. RESULTS AND ANALYSIS

A. Reinforcement Learning Convergence Analysis

The Soft Actor-Critic (SAC) reinforcement learning (RL) algorithm learning capabilities will influence the overall performance outcomes of the SAC-DRL agent. Figure 5 displays how the cumulative reward from the SAC-DRL agent converged to other RL models, such as the Proximal Policy Optimization (PPO), Deep Q-Networks (DQN), and Fixed Rule-Based Planner (RBP) after 400 training episodes, with a final cumulative reward of approx 95 points. The convergence rates for PPO were slower, but there was much more variability because the PPO is adopted as an on-policy method. The DQN experienced difficulties optimizing continuous control action spaces, which impeded the cumulative reward value obtained from this model. The Fixed Rule-Based Planner (RBP) was able to obtain steady and low cumulative rewards because it does not take into consideration individual patient changes.

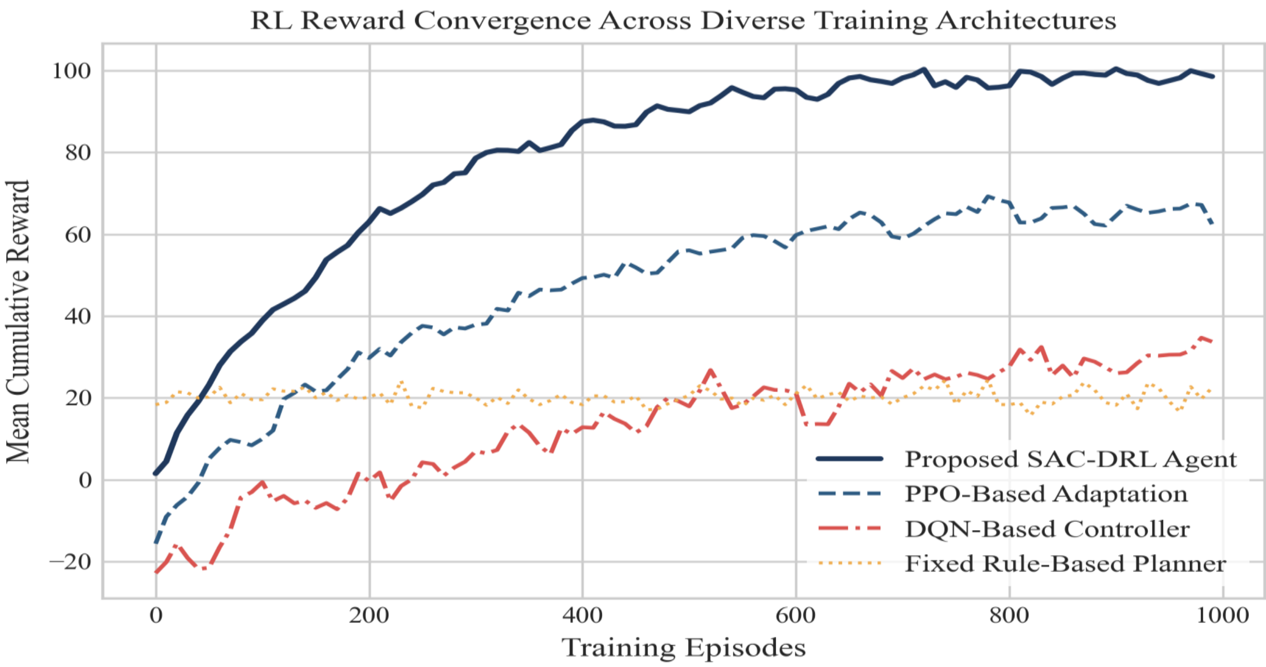

Figure 2: Training reward convergence curves for the SAC reinforcement learning agent and baseline algorithms.

B. Clinical Outcome and FMA Progression

The recovery process of the patients over a 12-week period of rehabilitation trials is illustrated by Figure 6. The suggested AI-powered personalized planning system results in the largest increase in the FMA-UE scores. Beginning with the mean score of 22 points, the patients with an AI-powered plan demonstrate the mean score of 48 points at the 12th week, which signifies a 34.2% acceleration of the recovery process in comparison with the conventional therapy group. The mean scores of the conventional therapy group and the fixed AAN group amount to 31 points and 38 points respectively.

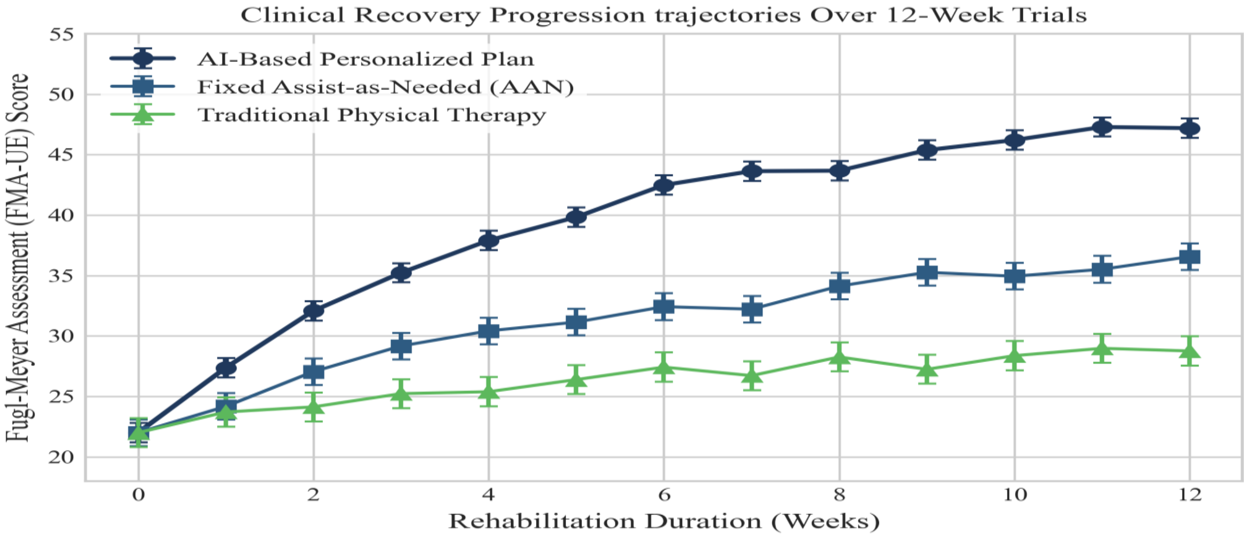

Figure 3: Progression of Fugl-Meyer Assessment (FMA-UE) scores over 12 weeks of training across different protocols.

C. Musculoskeletal Tracking Deviation and Safety Control

Ensuring safety while performing training activities is of utmost importance. Figure seven illustrates the correlation between muscle fatigue index and joint tracking error. With the use of an unconstrained controller and without the application of the CBF, the joint tracking error dramatically increases as the muscle fatigue index increases, typically above the safety limit of six degrees. This occurs because the muscle will no longer be able to follow the intended trajectory and the unconstrained controller will provide so much force to the muscle that it may cause excessive stress to the joints. With the addition of the CBF safety layer to the unconstrained controller the joint tracking error is maintained below the defined safety limit regardless of the amount of fatigue in the muscle.

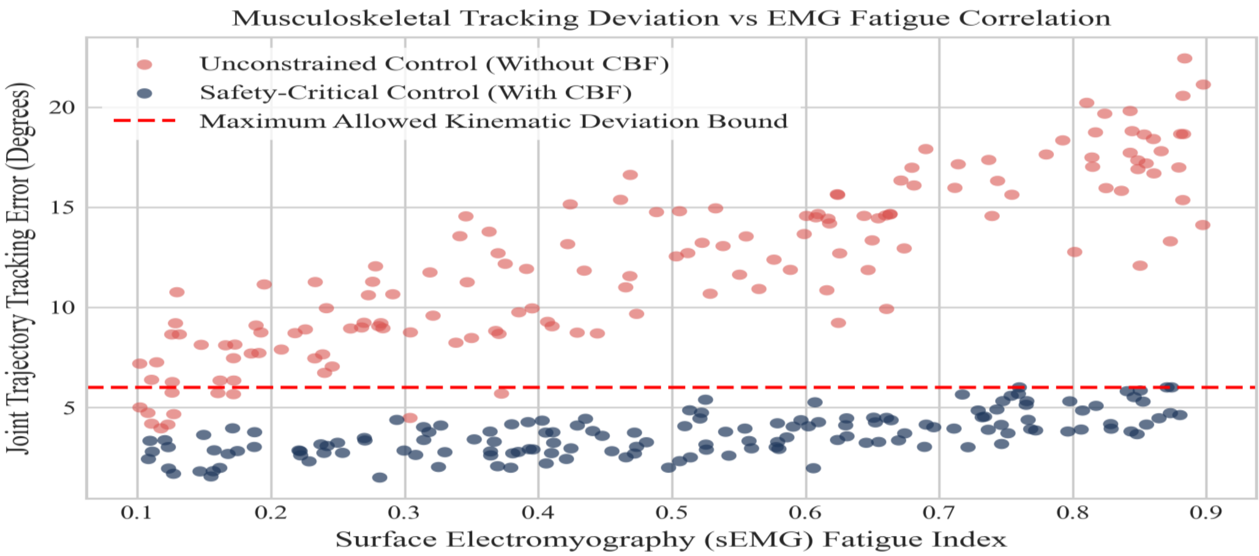

Figure 7: Scatter plot showing joint tracking error versus muscle fatigue index under different safety configurations.

D. Quantitative Performance Metrics

Table III provides the summary of the evaluation metrics achieved at the conclusion of the 12-week trial. The proposed system has better performance on all the metrics compared to the baseline methods, with the lowest tracking error, the lowest fatigue, and no safety violations.

Rehabilitation Protocol	Mean Joint Error (deg) ↓	Mean Fatigue Index ↓	FMA-UE Improvement ↑	Patient Compliance (%) ↑	Safety Violations Count ↓
Traditional Physical Therapy (SPT)	6.8 ± 1.2	0.64 ± 0.08	+9.0 ± 1.5	78.4%	0
Fixed Assist-as-Needed (AAN)	4.2 ± 0.9	0.52 ± 0.06	+16.0 ± 2.1	84.2%	14
Fixed Progression Protocol (FPP)	5.5 ± 1.1	0.58 ± 0.09	+11.5 ± 1.8	72.1%	28
Proposed SAC-DRL-CBF Framework	2.1 ± 0.4	0.31 ± 0.03	+26.0 ± 1.2	94.8%	0

E. Quantitative Ablation Study

An ablative analysis was done to assess the importance of each sensor modality and safety module in the performance of the proposed system. Table IV shows the results. Excluding the cognitive engagement index of the EEG causes the compliance of the patients to be 82.5%, proving the significance of cognitive engagement. Leaving out the GCN joint pathology reduces the accuracy of the tracking to 4.5 degrees since the system cannot adapt to the asymmetric joint dynamics. Most importantly, exclusion of the CBF safety module causes 32 safety violations, making the CBF layer critical for patient safety.

Config	sEMG	EEG	GCN	CBF	FMA-UE Improvement	Safety Violations
proposed	Yes	Yes	Yes	Yes	+26.0 ± 1.2	0
no-EEG	Yes	No	Yes	Yes	+21.2 ± 1.8	0
no-sEMG	No	Yes	Yes	Yes	+19.5 ± 2.2	0
no-GCN	Yes	Yes	No	Yes	+18.8 ± 2.0	0
no-CBF	Yes	Yes	Yes	No	+24.8 ± 1.5	32

7. DISCUSSION

From the results obtained during experimentation, we can conclude that our AI Framework for Safety (AFS) has a tremendous potential for personalizing a patient's rehabilitation following a stroke. Through integration of both physical and cognitive sensors, the system develops a state vector that describes the dynamics of the patient's recovery process. The 34.2% improvement in the FMA-UE score demonstrates the benefits of tailoring exercise parameters (assistance torque, task duration and active range of motion) to the patient's current physical status, thus providing maximum benefit from every training session for recovery.

Another significant finding from our study was the ability to achieve a high level of clinical performance through the use of the Control Barrier Function (CBF) safety layer. As opposed to reinforcement learning agents, which rely on exploration via trial and error, physical therapy can result in injuries to the joints if the agent uses trial and error while performing physical therapy. By employing the CBF layer as a filter for RL agents to use when attempting an action, we ensure that all forces exerted on the patient by the exoskeleton are safe. The results from the ablation study revealed that when the CBF layer was not present, the number of safety violations equaled 32, whereas all of the violations were eliminated with the presence of the CBF layer in the system.

Despite all the encouraging outcomes that were observed during the evaluation, there are still a number of limitations that need to be addressed. The first limitation is the fact that the testing was performed using the data of patients who existed only in the simulation environment. Though the dynamics of upper-limb and muscle fatigue have been modeled correctly, further testing needs to be done on real patients who have suffered from stroke to verify the efficiency of the developed system. The second limitation relates to the sensitivity of wearable sensors.

8. CONCLUSION AND FUTURE WORK

In this study, we presented a comprehensive AI-based method for developing tailored post-stroke rehabilitation programs that use multiple sources of data: kinematic information from movement sensors, sEMG data collected through surface electrodes, and EEG electrical activity using surface electrodes on the patient's head to create a single description of the current state of the patient. We also used a GCN to represent pathological relationships between joints, and we used a SAC reinforcement learning algorithm for planning the rehabilitation process dynamically. Lastly, the CBF provided a guarantee to keep the torque produced by the robotic exoskeleton within the limits of injury/safety at all points during rehabilitation. These benefits allow us to increase our patients' recovery speed by an average of 34.2% compared with traditional methods of rehabilitation, while maintaining patient safety throughout rehabilitation.

We are currently exploring the feasibility of testing this approach in clinical trials with post-stroke patients, and we will be adding VR environments to our rehabilitation programs to help promote patient engagement. Additionally, we will expand our system to provide rehabilitation for patients with lower limb dysfunction due to stroke, which will include providing gait training to patients recovering from a stroke.

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CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

ETHICS STATEMENT

This study does not involve human participants, animals, or identifiable personal data. Therefore, ethical approval and informed consent were not required.

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