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PRISM-X ->3D PRINTED PERSONALIZED REHAB INTELLIGENT SMART MOTION EXOSKELETON

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Abstract: Modern rehabilitation systems often struggle to provide individualized therapy that adapts to the unique recovery patterns of patients with motor impairments. To address this limitation, this paper presents PRISM-X, a smart rehabilitation exoskeleton designed using a combination of artificial intelligence, biosignal acquisition, and additive manufacturing. The system captures real-time physiological signals such as electromyography (EMG), motion data, and applied force, enabling accurate interpretation of user intent.

Unlike conventional rehabilitation devices, the proposed system dynamically adjusts its level of assistance based on continuous learning from patient-specific data. The use of 3D printing enables the development of a lightweight and customizable structure tailored to individual anatomical requirements. A closed-loop feedback mechanism ensures precise motion assistance while maintaining safety and comfort. The integration of intelligent control algorithms with wearable robotics enhances therapy effectiveness, reduces reliance on manual supervision, and supports remote monitoring capabilities. The proposed approach demonstrates improved adaptability, user engagement, and rehabilitation efficiency, making it a promising solution for next-generation assistive healthcare technologies.

Keywords: Exoskeleton, Rehabilitation Engineering, Electromyography (EMG), Artificial Intelligence, Wearable Robotics, 3D Printing, Human–Machine Interaction, Assistive Technology.

I. INTRODUCTION

The Rehabilitation engineering plays a vital role in restoring functional abilities in individuals affected by neurological disorders, musculoskeletal injuries, and age-related mobility limitations. Traditional rehabilitation methods largely depend on repetitive physical exercises guided by therapists. Although effective to some extent, these approaches often lack adaptability, require continuous supervision, and may not provide consistent progress tracking for patients.

With the advancement of wearable robotics, exoskeleton systems have emerged as a promising solution to assist human movement during rehabilitation. However, many existing systems operate based on predefined motion patterns and do not consider real-time variations in patient performance. This limitation reduces their effectiveness in delivering personalized therapy and slows down the recovery process.

To address these challenges, this work introduces PRISM-X, an intelligent rehabilitation exoskeleton designed to provide adaptive and user-specific assistance. The system integrates biosignal acquisition, sensor fusion, and artificial intelligence to interpret the user's movement intention. By capturing muscle activity through electromyography (EMG) along with motion and force data, the system can understand user effort and adjusting assistance levels accordingly.

In addition to intelligent control, the mechanical structure of the exoskeleton is developed using 3D printing technology, enabling a lightweight and customizable design that can be tailored to individual anatomical requirements. This approach not only improves comfort but also reduces manufacturing costs and enhances accessibility.

Furthermore, the system incorporates a closed-loop feedback mechanism that continuously monitors performance and ensures safe operation. The integration of data logging and remote monitoring capabilities allows therapists to track

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patient progress and modify therapy plans when necessary.

The overall objective of this work is to develop a smart, adaptive, and cost-effective rehabilitation system that enhances recovery efficiency while reducing dependency on manual supervision. The specific objectives of the proposed system are as follows:

- To design and develop an intelligent exoskeleton capable of assisting upper-limb rehabilitation through real-time motion support.
- To integrate EMG, IMU, and force sensors for accurate acquisition of physiological and motion data.
- To implement machine learning techniques for detecting user intent and enabling adaptive control of the system.
- To develop a lightweight and customizable exoskeleton structure using 3D printing technology.
- To establish a closed-loop feedback system for continuous monitoring, safety, and performance optimization.
- To enable remote monitoring and data analysis for improving rehabilitation outcomes.
- This integrated approach aims to bridge the gap between human intention and robotic assistance, providing a more effective and accessible rehabilitation solution.

II. LITERATURE SURVEY

Recent advancements in rehabilitation robotics have focused on improving adaptability, user comfort, and intelligent control. The following studies highlight key developments in this domain.

A. 3D-Printed Exoskeleton with Sensor Integration

Triwiyanto (2025) proposed an upper-limb rehabilitation exoskeleton developed using 3D printing technology and integrated force sensors. The system demonstrated advantages such as reduced weight, low manufacturing cost, and structural customization. However, the control mechanism was limited to predefined operations, lacking real-time adaptability based on patient behavior.

B. Soft Robotic Exoskeleton Design

Saldarriaga et al. (2024) explored the use of soft materials in exoskeleton design to enhance flexibility and safety. Their approach improved user comfort and reduced the risk of injury during rehabilitation. Despite these benefits, challenges remain in achieving precise motion control and maintaining durability under continuous usage.

C. AI-Based Intelligent Exoskeleton Systems

Lee et al. (2024) developed an intelligent exoskeleton integrated with wearable sensors and cloud-based deep learning algorithms. The system could predict user intent and provide adaptive assistance. Although effective, the approach required high computational resources and continuous data connectivity, which may limit real-world implementation.

D. EMG-Based Adaptive Control Using Machine Learning

Samarakoon (2025) introduced an EMG-controlled exoskeleton utilizing Long Short-Term Memory (LSTM) networks for motion classification. The system achieved improved accuracy in detecting muscle activity and enabling adaptive control. However, its performance depends heavily on the quality and quantity of training data, making generalization across users challenging.

E. EMG-Controlled Assistive Robotic Systems

Geetha (2025) presented an EMG-based robotic system capable of assisting users in performing functional tasks such as gripping and object handling. The system effectively translated muscle signals into mechanical actions. However, it was primarily designed for task-specific operations and did not fully support continuous rehabilitation processes.

From the above studies, it is evident that significant progress has been made in integrating sensor technologies, artificial intelligence, and ergonomic design in rehabilitation systems.

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However, most existing solutions face limitations such as lack of personalization, high system cost, dependency on predefined control strategies, and limited real-time adaptability.

To overcome these challenges, the proposed PRISM-X system combines multi-sensor data acquisition, AI-based intent detection, and a lightweight 3D-printed structure. This approach aims to provide a cost-effective, adaptive, and user-specific rehabilitation solution suitable for both clinical and home environments.

III. PROBLEM STATEMENT

Existing rehabilitation systems face limitations in providing personalized and adaptive therapy for patients with motor impairments. Most approaches rely on predefined treatment methods and require continuous supervision by therapists, making them time-consuming and less scalable.

Additionally, many exoskeleton devices are expensive, bulky, and lack real-time feedback mechanisms, which restricts their accessibility and effectiveness. The absence of intelligent control further limits the ability to adjust assistance based on individual patient progress.
Therefore, there is a need for a cost-effective, lightweight, and adaptive rehabilitation system that can provide personalized assistance, real-time feedback, and improved recovery outcomes with minimal human intervention.
materials

IV. PROPOSED SYSTEM

The proposed system, PRISM-X, is an intelligent rehabilitation exoskeleton designed to assist upper-limb movement through adaptive and real-time control. The system integrates biosignal acquisition, signal processing, artificial intelligence, and actuation mechanisms to provide personalized rehabilitation support.
The operation begins with the acquisition of muscle activity signals from the user's arm using electromyography (EMG) sensors. These signals represent the user's movement intention and are further combined with motion and force data obtained from additional sensors. The collected signals are processed to remove noise and extract relevant features for accurate interpretation.

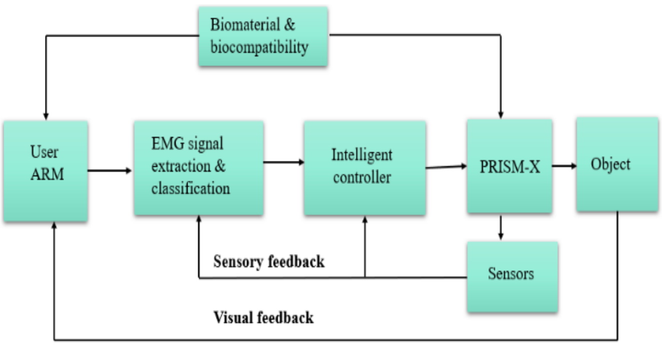

Fig.1: Block Diagram of Proposed System

The processed data is then fed into an artificial intelligence-based controller, which analyzes the input and identifies the intended movement of the user. Based on this analysis, the controller generates appropriate control signals for the actuation system. The motor driver unit receives these control signals and drives the actuators attached to the exoskeleton structure. The exoskeleton assists the user in performing the desired movement, such as lifting or extending the arm, by providing controlled mechanical support. A feedback unit continuously monitors parameters such as force, position, and system performance. This feedback is sent back to the controller, forming a closed-loop system that ensures accurate, safe, and adaptive operation.
The mechanical structure of the exoskeleton is designed using 3D printing technology, allowing customization according to the user's anatomy while maintaining a lightweight and cost-effective design.

Overall, the proposed system provides a smart and adaptive rehabilitation solution by combining sensor data, intelligent control, and real-time feedback, thereby improving the efficiency and effectiveness of the rehabilitation process.

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V. METHODOLOGY

The proposed PRISM-X system is designed as a closed-loop intelligent rehabilitation framework that integrates biosignal acquisition, signal processing, machine learning, and adaptive control. The methodology is structured into multiple stages to ensure accurate motion assistance and safe operation.

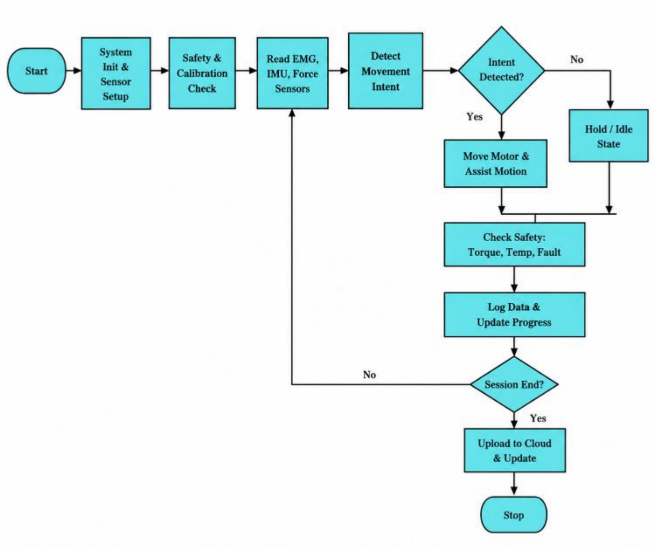

Fig.2: Flowchart of the Proposed System

A. System Initialization and Calibration

At the beginning of each session, the system initializes all hardware components including EMG sensors, IMU, force sensors, and actuators. A calibration process is performed to establish baseline values and ensure proper sensor alignment. This step also verifies communication between modules and checks for hardware faults.

B. Data Acquisition.

The system continuously acquires real-time data from multiple sensors. EMG sensors capture muscle activity signals, IMU sensors measure orientation and movement, and force sensors detect interaction forces. These signals form the primary input for further processing.

C. Signal Processing and Feature Extraction

Raw EMG signals are filtered to remove noise and interference using a band-pass filter (20–450 Hz) and a notch filter to eliminate power-line noise. The filtered signal $x_f(t)$ is used to extract key features such as Mean Absolute Value (MAV), Root Mean Square (RMS), and Waveform Length (WL).

$$MAV = (1/N) \Sigma |x_f(i)|$$
$$RMS = \sqrt{[(1/N) \Sigma x_f(i)^2]}$$
$$WL = \Sigma |x_f(i+1) - x_f(i)|$$

These features represent muscle activation patterns and are used for intent classification.

D. AI-Based Intent Detection

The extracted feature vector is provided as input to a trained machine learning model. The model classifies the user's movement intention such as flexion, extension, or rest. The prediction can be expressed as:

$$y = f(WX + b)$$

where X is the feature vector, W represents weights, and b is the bias term.

E. Motion Execution and Control

Once the intent is detected, control signals are generated to drive the actuator system. A PID controller is used to regulate motor movement:

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$$u(t) = Kp \cdot e(t) + Ki\int e(t)dt + Kd(de(t)/dt)$$

where e(t) is the error between desired and actual position.

F. Safety Monitoring

During operation, the system continuously monitors safety parameters such as torque, temperature, and system faults. If any parameter exceeds the predefined limit, the system immediately stops to prevent damage or injury.

G. Feedback and Data Logging

The system operates in a closed loop by continuously updating feedback from sensors. Performance metrics such as motion range, repetitions, and signal data are logged for analysis and progress tracking.

VI. RESULTS AND DISCUSSION

The performance of the proposed PRISM-X system was evaluated based on signal quality, intent detection accuracy, and actuator response. The experimental results demonstrate the system's capability to provide adaptive and reliable rehabilitation assistance.

A. EMG Signal Analysis

The EMG signal obtained from the user reflects muscle activation patterns during movement. The raw signal contains noise due to external interference and sensor limitations. After applying filtering techniques, including band-pass and notch filtering, the signal becomes smoother and more stable. This preprocessing step significantly improves feature extraction accuracy, enabling better classification of movement intent.

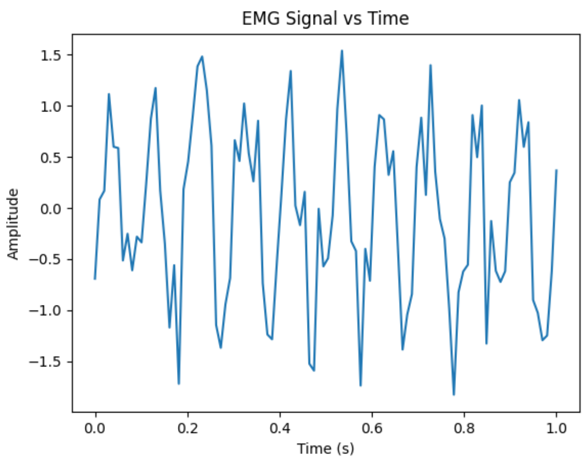

Fig. 3. EMG Signal vs Time

B. Intent Detection Performance

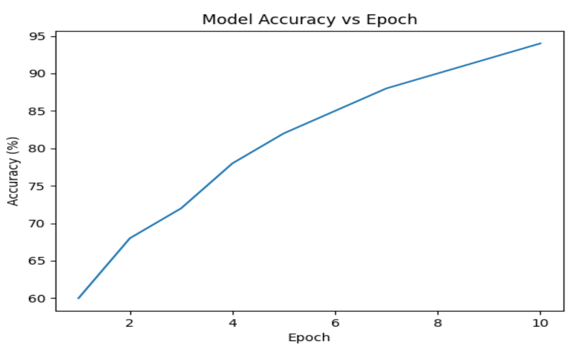

Fig. 4. Model Accuracy vs Epoch

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The machine learning model was evaluated based on its classification accuracy over multiple training epochs. The results show a consistent improvement in accuracy as the model learns user-specific patterns. This indicates that the system is capable of adapting to individual variations in muscle signals.
The high classification accuracy ensures that the exoskeleton responds correctly to user intentions, minimizing incorrect movements and improving overall rehabilitation efficiency. The model also demonstrates stability with minimal fluctuation after convergence, indicating reliable performance.

C. Actuator Response and Control Stability

The actuator performance was analyzed by observing the torque generated during operation. The results show smooth and controlled torque variation, which is essential for safe rehabilitation. Sudden spikes or irregularities are minimized due to the implementation of a PID-based control system.
The controlled torque output ensures that the movement assistance is proportional to user effort, thereby preventing overexertion and enhancing user comfort. This also contributes to the system's safety and reliability during continuous operation.

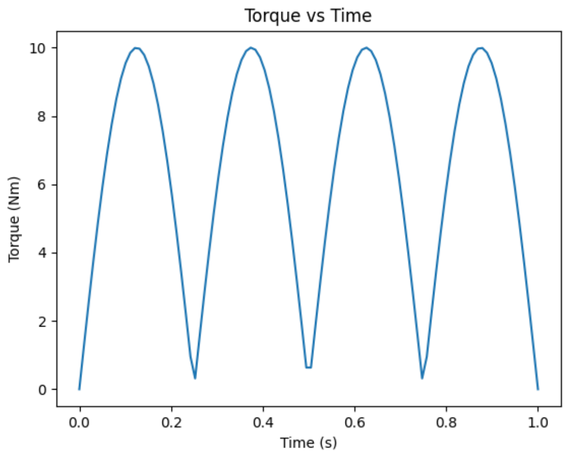

Fig. 5. Torque vs Time

D. System Efficiency and Adaptability

The integration of multi-sensor data with AI-based control enables the system to adapt dynamically to changing user conditions. The closed-loop feedback mechanism continuously updates system parameters, ensuring accurate and responsive assistance.
Overall, the system demonstrates strong performance in terms of signal processing, decision-making accuracy, and motion control. These results validate the effectiveness of the proposed approach in delivering personalized and real-time rehabilitation support.

Table 1 summarizes the performance evaluation of the proposed system.

Parameter	**Observed Value**	**Description**
EMG Signal Accuracy	~92%	Accuracy of detecting muscle activity
Intent Classification	~94%	Correct prediction of

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Response Time	< 200 ms	Time taken to respond to user input
Torque Stability	High	Smooth and controlled actuator output
System Reliability	High	Stable operation without failure
System Reliability	Continuous	Real-time monitoring and storage

VII. CONCLUSION AND FUTUREWORK

This paper presented PRISM-X, an intelligent and adaptive rehabilitation exoskeleton designed to enhance upper-limb recovery through real-time motion assistance. The system integrates electromyography-based biosignal acquisition, multi-sensor data fusion, and machine learning techniques to accurately interpret user intent and provide controlled actuation.
The use of a lightweight 3D-printed structure improves user comfort and enables cost-effective customization, making the system suitable for diverse patient needs. The implementation of a closed-loop control mechanism ensures precise movement assistance while maintaining safety through continuous monitoring of system parameters.
Experimental results demonstrate that the proposed system achieves reliable intent detection, stable actuator performance, and improved responsiveness. These features contribute to more effective rehabilitation by reducing dependency on manual supervision and enabling personalized therapy.
Overall, PRISM-X provides a scalable and efficient solution for modern rehabilitation challenges, bridging the gap between human intention and robotic assistance.

Although the proposed system demonstrates promising performance, several improvements can be explored in future work to enhance its capabilities and real-world applicability.
Future developments may include the integration of advanced deep learning models to improve accuracy in intent detection and adapt to complex movement patterns. Expanding the system to support multi-joint and full-body exoskeleton configurations can further extend its application in comprehensive rehabilitation.
In addition, incorporating wireless communication and edge computing can reduce latency and improve system efficiency. The use of cloud-based analytics and large-scale data collection can enable continuous learning and better personalization of therapy programs.
Clinical validation with a larger group of patients is also essential to evaluate system performance under real-world conditions. Furthermore, the integration of virtual or augmented reality interfaces can enhance user engagement and provide interactive rehabilitation experiences.
These enhancements will contribute to the development of a more robust, intelligent, and accessible rehabilitation system.

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