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Development of Ai-Driven Systems for Real-Time Joint Movement Detection and Correction in Frozen Shoulder Therapy Using Sensor-Based Shoulder Rehabilitation Devices

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Abstract

Frozen shoulder, or adhesive capsulitis, is a common musculoskeletal disorder characterized by progressive pain, stiffness, and restricted range of motion that significantly impairs functional ability and quality of life. Recent advancements in artificial intelligence and sensor-based technologies have enabled the development of intelligent rehabilitation systems capable of real-time joint movement detection and correction. Wearable sensors, such as inertial measurement units, electromyography sensors, and flexible strain sensors, capture continuous biomechanical data that are processed using machine learning algorithms to analyze movement patterns, detect abnormalities, and provide immediate corrective feedback. This improves exercise accuracy and reduces compensatory movements. These AI-driven systems support personalized rehabilitation by adapting therapy protocols based on patient performance and recovery progression. They also enable remote monitoring and reduce dependency on constant clinical supervision. Integration with robotic-assisted devices and virtual reality platforms further enhances engagement, precision, and therapeutic outcomes. Although challenges, such as cost, technical complexity, and data privacy remain, ongoing advancements are expected to improve accessibility and clinical adoption. AI-driven rehabilitation systems, therefore, represent a promising solution for effective and efficient management of frozen shoulder.

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INTRODUCTION

Frozen shoulder, also known as adhesive capsulitis, is a prevalent musculoskeletal disorder characterized by progressive stages of pain, stiffness, and eventual recovery, typically involving inflammatory, freezing, frozen, and thawing phases that significantly impair shoulder mobility and functional capacity, thereby affecting activities of daily living and quality of life. Despite the effectiveness of conventional physiotherapy interventions, such as joint mobilization, stretching, and electrotherapy, these approaches are often limited by intermittent supervision, lack of continuous monitoring, and variability in patient adherence, which restricts optimal treatment outcomes and delays recovery progression. Moreover, recent surveys of clinical practice indicate that physiotherapy for frozen

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shoulder is frequently delivered in episodic sessions with reliance on patient-reported outcomes and manual assessment, leading to inconsistencies in treatment personalization and reduced ability to track real-time biomechanical changes [1]. In addition, systematic reviews highlight that while conventional modalities, such as electrophysical agents and exercise therapy, provide symptomatic relief, their effectiveness varies widely due to differences in application, patient compliance, and absence of continuous feedback mechanisms. Consequently, the integration of artificial intelligence (AI) into rehabilitation has emerged as a transformative approach that enhances precision, personalization, and efficiency in managing frozen shoulder by leveraging advanced computational techniques and sensor-based technologies. AI-driven rehabilitation systems utilize wearable sensors, inertial measurement units (IMUs), and motion tracking devices to capture detailed kinematic and biomechanical data during patient movement, enabling objective assessment of joint range of motion, movement smoothness, and functional performance, which are critical parameters for evaluating rehabilitation progress. Furthermore, these systems incorporate data acquisition modules that continuously collect real-time physiological and motion-related data, thereby overcoming the limitations of periodic clinical assessments and providing a comprehensive understanding of patient performance outside clinical settings [2]. The collected data are then processed using machine learning algorithms and AI-based analytical models that identify movement patterns, detect abnormalities, and predict rehabilitation outcomes, allowing for adaptive and individualized therapy protocols tailored to each patient's condition and recovery stage. In addition, virtual reality (VR) and AI-integrated rehabilitation platforms have demonstrated significant improvements in pain reduction, joint mobility, and quality of life among frozen shoulder patients by providing immersive, interactive, and engaging therapeutic environments that enhance patient motivation and adherence to prescribed exercises. Similarly, wearable sensor-based virtual rehabilitation systems have been shown to effectively guide patients through structured exercise programs while simultaneously monitoring performance metrics and providing real-time feedback, thereby facilitating motor learning and functional recovery. Robotic-assisted rehabilitation systems further extend the capabilities of AI-driven approaches by enabling precise control of shoulder movements, replication of natural biomechanical patterns, and correction of compensatory motions, which are essential for restoring normal scapulohumeral rhythm and preventing secondary complications. Importantly, the feedback interface in AI-driven systems plays a crucial role in delivering actionable insights to both patients and clinicians through visual dashboards, alerts, and performance analytics, ensuring timely intervention and continuous adjustment of therapy plans based on real-time data. This closed-loop architecture, consisting of sensors, data acquisition modules, processing algorithms, and feedback interfaces, forms the conceptual foundation of AI-driven rehabilitation systems, as illustrated in Figure 1, where each component interacts dynamically to enable continuous monitoring, accurate assessment, and adaptive correction of patient movements. Overall, AI-driven rehabilitation systems represent a paradigm shift from traditional physiotherapy by enabling data-driven decision-making, enhancing treatment precision, improving patient engagement, and facilitating faster and more effective recovery in individuals with frozen shoulder, thereby highlighting their potential to revolutionize musculoskeletal rehabilitation practices in modern healthcare settings [3].

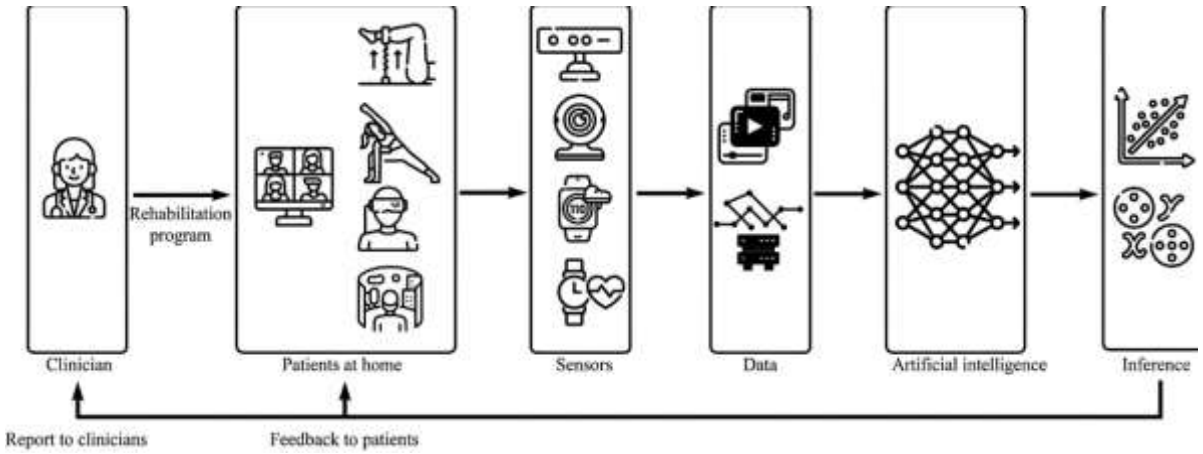


Figure 1. Conceptual architecture of AI-driven rehabilitation system.

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PATHOPHYSIOLOGY OF FROZEN SHOULDER

Frozen shoulder, or adhesive capsulitis, is a complex musculoskeletal condition involving capsular inflammation, progressive fibrosis, and reduced synovial lubrication, all of which contribute to significant restriction in glenohumeral joint mobility and functional impairment, and the pathological process typically begins with an inflammatory response within the synovial lining, leading to synovial hyperplasia, increased vascularity, and pain, which subsequently progresses to fibrotic remodeling characterized by collagen deposition, capsular thickening, and contraction, thereby limiting both active and passive range of motion. The inflammatory phase is associated with cytokine-mediated processes and immune system activation, which stimulate fibroblast proliferation and excessive extracellular matrix formation, further exacerbating capsular stiffness and joint restriction [4]. Additionally, histopathological findings demonstrate synovial inflammation followed by fibrosis of the joint capsule, confirming that frozen shoulder is not merely a mechanical disorder but a biologically driven condition involving both inflammatory and fibrotic pathways. As the disease progresses, the reduction in synovial fluid and lubrication within the joint contributes to increased friction and resistance during movement, thereby intensifying stiffness and discomfort, particularly during shoulder elevation and rotational activities. Furthermore, capsular contracture and thickening of the coracohumeral ligament reduce joint volume and alter normal biomechanics, resulting in a significant decrease in joint play and functional mobility. Disruptions in scapulohumeral rhythm are a critical biomechanical consequence of frozen shoulder, as the coordinated movement between the scapula and humerus becomes altered due to restricted glenohumeral motion, leading patients to adopt compensatory strategies, such as excessive scapular elevation or trunk movement, which may temporarily facilitate motion but ultimately contribute to abnormal movement patterns, muscle imbalance, and increased risk of secondary musculoskeletal complications if not corrected early. These compensatory mechanisms not only reduce the efficiency of shoulder function but also place additional stress on surrounding structures, thereby prolonging recovery and potentially worsening clinical outcomes. The progression of frozen shoulder is classically divided into three primary stages, namely the freezing stage, frozen stage, and thawing stage, each characterized by distinct pathological and clinical features that guide therapeutic decision-making and rehabilitation planning [5]. The freezing stage is marked by severe pain and gradual loss of motion due to active inflammation and synovitis, during which patients experience increasing discomfort and functional limitation, often accompanied by night pain and reduced tolerance to movement. This is followed by the frozen stage, where pain may decrease but stiffness becomes predominant due to established fibrosis and capsular contracture, significantly restricting joint mobility and limiting activities such as reaching, lifting, or dressing. Finally, the thawing stage involves gradual resolution of fibrosis and partial restoration of joint mobility, although recovery may take several months to years and may not always result in complete return to pre-condition function. Figure 2 conceptually illustrates this progression by mapping the three stages alongside their associated symptoms, including pain intensity, degree of stiffness, and functional limitations, thereby providing a structured framework for understanding disease evolution and guiding stage-specific rehabilitation strategies aimed at optimizing patient outcomes and preventing long-term disability [6, 7].

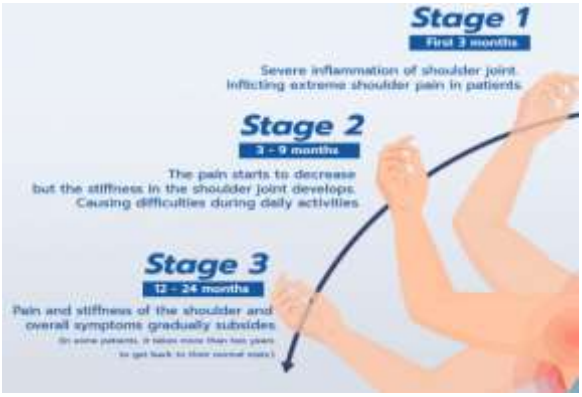


Figure 2. Stages of frozen shoulder progression.

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SENSOR-BASED REHABILITATION TECHNOLOGIES

Sensor-based rehabilitation technologies form the backbone of AI-driven rehabilitation systems by enabling continuous, objective, and high-resolution measurement of human movement, thereby overcoming the limitations of subjective clinical assessment and intermittent observation, and these technologies rely on wearable devices embedded with advanced sensing components that capture biomechanical and physiological parameters essential for evaluating joint function and guiding therapy. Wearable sensors are typically lightweight, non-invasive, and strategically placed on different segments of the upper limb, such as the trunk, upper arm, forearm, and wrist, to ensure accurate tracking of motion patterns during rehabilitation exercises. Among these, inertial measurement units (IMUs) are the most widely used sensors due to their ability to measure acceleration, angular velocity, and orientation in three-dimensional space, making them highly suitable for capturing joint kinematics in real time. IMUs typically integrate accelerometers and gyroscopes, and sometimes magnetometers, allowing precise estimation of limb position and movement dynamics, which is critical for assessing range of motion and movement quality in shoulder rehabilitation [8, 9]. In addition to motion tracking, electromyography (EMG) sensors play a vital role in monitoring muscle activation patterns by detecting electrical signals generated during muscle contraction, thereby providing insight into neuromuscular coordination, muscle fatigue, and recruitment strategies during rehabilitation exercises. EMG sensors are particularly valuable in identifying abnormal muscle activation and compensatory mechanisms, enabling clinicians and AI systems to design targeted interventions that improve muscle function and restore normal movement patterns. Furthermore, strain sensors and force sensors are used to detect joint displacement, mechanical stress, and interaction forces, which are essential for understanding joint loading conditions and ensuring safe execution of therapeutic movements. The integration of multiple sensor modalities, often referred to as sensor fusion, enhances the accuracy and reliability of data by combining complementary information from different sources, thereby enabling more robust analysis and interpretation of patient performance [10]. As illustrated in Figure 3, wearable shoulder rehabilitation devices incorporate these sensors in a compact and ergonomic design, with sensors strategically positioned to capture upper limb motion accurately while minimizing interference with natural movement, and such configurations enable continuous monitoring of joint angles, velocity, acceleration, and muscle activity during both clinical sessions and home-based rehabilitation. The data collected from these sensors serve as critical input for AI algorithms, which process the information using machine learning and deep learning techniques to classify movements, detect deviations from desired motion patterns, and provide real-time feedback to patients and clinicians. For instance, AI models trained on IMU data have demonstrated high accuracy in identifying different types of shoulder rehabilitation exercises, thereby enabling automated monitoring of exercise compliance and performance quality [11, 12].



Figure 3. Wearable shoulder rehabilitation device with embedded sensors.

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Table 1 further complements this discussion by categorizing the types of sensors used in shoulder rehabilitation systems and their respective functions, highlighting the critical role of IMUs in motion tracking, EMG sensors in muscle activity monitoring, and strain or force sensors in detecting joint displacement and interaction forces, which together provide a comprehensive understanding of both kinematic and kinetic aspects of movement. Accelerometers, as a component of IMUs, measure linear acceleration across multiple axes, while gyroscopes capture angular velocity, enabling precise calculation of joint angles and movement trajectories [13]. Similarly, EMG sensors quantify muscle activation signals, which can be analyzed to assess muscle coordination and detect early signs of fatigue or abnormal recruitment patterns. Strain sensors, on the other hand, measure deformation or displacement within the device or joint interface, providing valuable information about mechanical loading and movement amplitude [14]. The continuous data stream generated by these sensors enables the development of closed-loop rehabilitation systems, where real-time feedback is provided to patients through visual, auditory, or haptic interfaces, facilitating immediate correction of movement errors and enhancing motor learning. Moreover, the ability to monitor patients remotely using wearable sensor technology supports telerehabilitation, allowing patients to perform exercises at home while maintaining clinical oversight, thereby improving accessibility, adherence, and overall treatment outcomes [15, 16].

Table 1. Types of sensors used in shoulder rehabilitation systems.

Sensor type	Function	Measured parameters	Application in rehabilitation
Inertial Measurement Unit (IMU)	Tracks motion and orientation	Acceleration, angular velocity, joint angles	Monitors range of motion and movement patterns during exercises.
Accelerometer	Measures linear motion	Linear acceleration along multiple axes	Detects movement speed and direction.
Gyroscope	Measures rotational motion	Angular velocity	Assesses rotational movements of the shoulder joint.
Magnetometer	Detects orientation relative to magnetic field	Orientation, heading	Enhances motion tracking accuracy when combined with IMU.
Electromyography (EMG) Sensor	Monitors muscle activity	Electrical signals from muscles	Evaluates muscle activation and coordination.
Strain Sensor	Measures deformation or stretch	Displacement, strain	Detects joint movement and mechanical stress.
Force Sensor	Measures applied force	Force, pressure	Assesses interaction forces during exercises.
Flex Sensor	Detects bending motion	Degree of bending	Tracks joint flexion and extension.
Pressure Sensor	Measures pressure distribution	Contact pressure	Evaluates load distribution and posture.
Optical Sensors (e.g., Cameras, Depth Sensors)	Captures visual motion data	Position, movement trajectory	Used in motion capture and virtual rehabilitation systems.

AI-BASED MOVEMENT DETECTION

Artificial intelligence (AI) plays a crucial role in analyzing sensor data in modern rehabilitation systems by transforming raw biomechanical signals into clinically meaningful insights, thereby enabling accurate detection and classification of shoulder movements and enhancing the effectiveness of therapy [17, 18]. AI-driven systems utilize data collected from wearable sensors, such as inertial measurement units (IMUs), to identify patterns in joint motion, which allows automated monitoring of rehabilitation exercises and ensures that patients perform movements correctly and consistently. Deep learning models, particularly convolutional neural networks (CNNs), are widely employed in this context due to their ability to automatically extract spatial features from complex sensor data, making them highly effective in recognizing different exercise patterns without the need for manual feature engineering. Recurrent neural networks (RNNs), including long short-term memory (LSTM) networks,

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further enhance this capability by capturing temporal dependencies in sequential motion data, enabling accurate analysis of dynamic movements such as shoulder abduction and rotation [19]. These models work synergistically to process multidimensional time-series data obtained from sensors, thereby improving classification accuracy and reliability in rehabilitation systems. The operational workflow of AI-driven rehabilitation systems, as illustrated in Figure 4, typically consists of several key stages including data acquisition, pre-processing, feature extraction, and classification, each of which plays a vital role in converting raw sensor signals into actionable clinical information [20, 21].

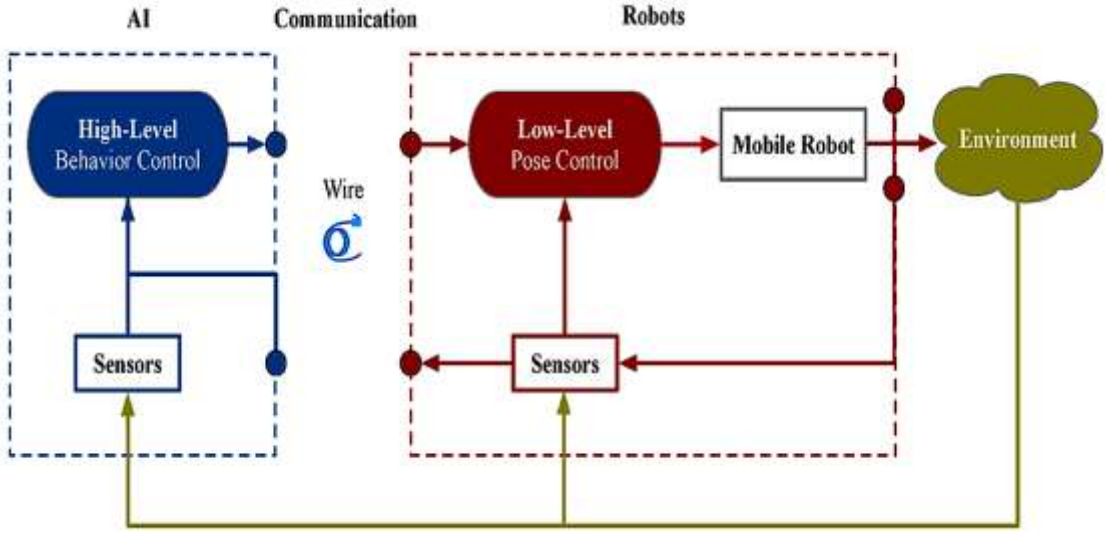


Figure 4. Workflow of AI-based movement detection system.

During the data acquisition phase, wearable sensors continuously capture motion-related data, such as acceleration, angular velocity, and joint orientation, while the patient performs rehabilitation exercises, ensuring comprehensive and real-time monitoring of movement [22]. This is followed by pre-processing, where noise reduction techniques, filtering algorithms, and segmentation methods are applied to remove irrelevant or erroneous data, thereby improving the quality and reliability of the dataset used for analysis. Feature extraction is then performed to derive meaningful statistical and biomechanical features, such as mean, variance, peak values, and frequency components from the raw sensor data, which are essential for distinguishing between different movement patterns [23]. Finally, in the classification stage, machine learning and deep learning models analyze the extracted features to categorize movements into predefined exercise classes and detect deviations from normal patterns, thereby enabling automated assessment of exercise performance and identification of errors. Deep learning-based classification systems have demonstrated high accuracy in recognizing shoulder rehabilitation exercises, with studies reporting classification accuracies exceeding 90%, highlighting their potential for reliable and scalable implementation in clinical and home-based rehabilitation settings [24]. These systems not only classify exercises but also provide real-time feedback to patients, allowing immediate correction of improper movements and reducing the risk of injury or ineffective therapy. Furthermore, AI models can detect subtle variations in movement patterns that may not be easily observed by clinicians, thereby enabling early identification of compensatory behaviors and facilitating targeted interventions. Table 2 complements this discussion by comparing different machine learning algorithms used in rehabilitation systems based on parameters, such as accuracy, computational complexity, and suitability for real-time applications, thereby assisting researchers and clinicians in selecting appropriate models for system development [25]. Traditional machine learning algorithms, such as support vector machines (SVMs) and decision trees, are often used for their simplicity and lower computational requirements, making them suitable for resource-constrained environments, although they may require manual feature extraction and may not achieve the same level of accuracy as deep learning models [26]. In contrast, deep learning models, such as CNNs and RNNs, offer superior

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performance in handling large and complex datasets due to their ability to learn hierarchical and temporal features directly from raw data, although they require higher computational resources and larger datasets for training. Hybrid approaches that combine multiple algorithms or integrate sensor fusion techniques further enhance performance by leveraging the strengths of different models, thereby improving classification accuracy and robustness in diverse rehabilitation scenarios [27].

Table 2. Comparison of machine learning algorithms for movement detection.

Algorithm	Accuracy	Computational requirement	Advantages	Limitations	Applicability in rehabilitation
Support Vector Machine (SVM)	High (for small–medium datasets)	Moderate	Effective in high-dimensional data, good generalization	Requires feature engineering, less efficient for large datasets	Widely used for classifying movement patterns.
Decision Tree	Moderate	Low	Easy to interpret, fast computation	Prone to overfitting, lower accuracy	Useful for simple classification tasks.
Random Forest	High	Moderate to High	Reduces overfitting, robust performance	Increased complexity, less interpretable	Suitable for complex movement classification.
k-Nearest Neighbors (k-NN)	Moderate to High	Low (training), High (testing)	Simple implementation, no training phase	Slow for large datasets, sensitive to noise	Used for pattern recognition in motion data.
Naïve Bayes	Moderate	Low	Fast, efficient for real-time systems	Assumes feature independence, less accurate in complex data	Applicable for basic movement classification.
Artificial Neural Network (ANN)	High	High	Learns complex patterns, adaptable	Requires large datasets, computationally intensive	Suitable for advanced rehabilitation systems.
Convolutional Neural Network (CNN)	Very High	High	Automatic feature extraction, high accuracy	Requires large data and processing power	Ideal for sensor-based movement recognition.
Recurrent Neural Network (RNN / LSTM)	Very High	High	Handles sequential/time-series data effectively	Complex training, risk of overfitting	Best for analyzing continuous movement patterns.
Gradient Boosting (e.g., XGBoost)	Very High	High	High performance, handles complex data well	Computationally intensive, less interpretable	Used for precise movement classification.
Logistic Regression	Moderate	Low	Simple, interpretable, fast	Limited for complex patterns	Suitable for basic classification tasks.

REAL-TIME MOVEMENT CORRECTION MECHANISMS

Real-time feedback is a critical component of AI-driven rehabilitation systems because it ensures proper execution of therapeutic exercises and minimizes the occurrence of compensatory or incorrect movements, thereby improving treatment outcomes and reducing the risk of secondary injury [28]. Traditional rehabilitation often relies on delayed or subjective feedback from clinicians, whereas AI-based systems enable immediate and continuous evaluation of patient performance through integration with wearable sensors and intelligent algorithms. These systems collect real-time biomechanical data, such as joint angles, velocity, and muscle activity, which are instantly processed to assess movement quality and detect deviations from prescribed exercise patterns. One of the key advantages of real-time feedback is its ability to facilitate motor learning by providing patients with immediate corrective guidance, allowing them to adjust their movements during the execution of exercises rather than after completion, which significantly enhances skill acquisition and rehabilitation efficiency [29]. AI-driven systems deliver this feedback through multiple modalities, including visual displays, mobile

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applications, and haptic signals, each offering unique benefits in terms of user engagement and accessibility. Visual feedback may include graphical representations of joint motion, progress indicators, or real-time motion tracking, while mobile applications provide interactive platforms for monitoring performance and receiving personalized exercise recommendations. Haptic feedback, on the other hand, uses vibrations or tactile cues to alert patients when incorrect movements are detected, thereby enabling intuitive and immediate correction without the need for constant visual attention [30]. The feedback mechanism in AI-driven rehabilitation systems is typically structured as a closed-loop system, as illustrated in Figure 5, where sensor data is continuously acquired, analyzed, and used to generate corrective instructions that are delivered instantly to the patient, ensuring a dynamic and adaptive rehabilitation process. In this closed-loop architecture, the patient's movement serves as input, which is captured by sensors and processed by AI algorithms to evaluate performance in real time, and the resulting feedback is then provided to guide subsequent movements, creating a continuous cycle of assessment and correction. This iterative process not only improves movement accuracy but also enhances patient engagement by providing immediate and tangible responses to their actions, thereby increasing motivation and adherence to rehabilitation programs [31]. Moreover, real-time feedback systems can identify subtle abnormalities and compensatory strategies that may not be easily observable by clinicians during routine sessions, enabling early intervention and prevention of maladaptive movement patterns that could hinder recovery. For example, AI algorithms can detect asymmetrical movements, excessive trunk compensation, or reduced range of motion, and immediately alert the patient or clinician, thereby ensuring that corrective measures are implemented promptly [32]. This capability is particularly important in shoulder rehabilitation, where improper movement patterns can lead to further joint stress and delayed healing. In addition, real-time feedback supports remote rehabilitation or telerehabilitation by allowing patients to perform exercises at home while still receiving continuous guidance and monitoring, thereby extending the reach of healthcare services and improving accessibility for individuals who may have limited access to in-person therapy. The integration of AI with mobile and wearable technologies ensures that feedback is not only immediate but also personalized, as the system can adapt to the patient's progress, limitations, and specific rehabilitation goals [33].

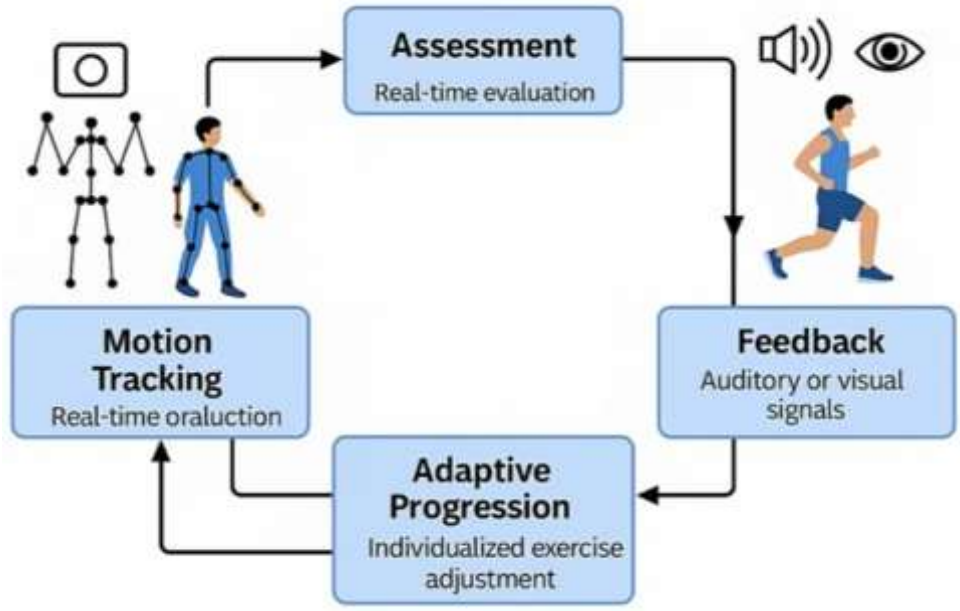


Figure 5. Real-Time Feedback Loop in Rehabilitation System.

ROBOTIC-ASSISTED REHABILITATION

Robotic-assisted rehabilitation systems have emerged as an advanced approach in modern physiotherapy by providing highly precise, controlled, and repeatable movements that enhance

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therapeutic outcomes, particularly in shoulder rehabilitation where complex joint mechanics require accurate guidance, and these systems are designed to assist patients in performing exercises with consistent trajectories while minimizing human error and variability associated with manual therapy [34]. Unlike conventional therapy, robotic devices can deliver intensive and repetitive training sessions with uniform accuracy, which is essential for promoting neuroplasticity, restoring motor function, and improving joint mobility in patients with musculoskeletal disorders. These systems can replicate natural joint motion by incorporating biomechanical models of the shoulder, thereby ensuring that movements follow physiological patterns and reducing the likelihood of abnormal or compensatory motion strategies that could hinder recovery. One of the most significant advantages of robotic-assisted rehabilitation is its ability to guide patient movements with high precision while maintaining safety and comfort, as robotic exoskeletons and end-effector devices are equipped with sensors and actuators that continuously monitor joint position, force, and movement dynamics, allowing real-time adjustments to ensure optimal performance. These systems often employ assist-as-needed control strategies, where the robot provides support only when required, encouraging active patient participation while preventing over-reliance on the device, thereby promoting motor learning and functional independence. Furthermore, robotic systems can be programmed to limit excessive or compensatory movements, such as scapular elevation or trunk deviation, ensuring that rehabilitation exercises target the intended muscles and joints effectively [35]. As illustrated in Figure 6, AI-integrated robotic shoulder rehabilitation systems combine robotic hardware with advanced artificial intelligence algorithms to create adaptive and personalized therapy environments, where the robot not only executes movements but also analyzes patient performance and adjusts assistance levels accordingly. AI algorithms process data from embedded sensors to evaluate parameters, such as range of motion, movement smoothness, and patient effort, enabling the system to dynamically modify exercise intensity, speed, and resistance based on individual progress and rehabilitation goals. This integration allows for the development of intelligent rehabilitation platforms that continuously learn from patient data and optimize therapy protocols in real time, thereby enhancing treatment efficiency and effectiveness [36].



Figure 6. AI-integrated robotic shoulder rehabilitation system.

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In addition, robotic-assisted systems facilitate objective assessment of patient performance by providing quantitative data on movement accuracy, force generation, and joint kinematics, which can be used to track progress over time and guide clinical decision-making. This data-driven approach reduces reliance on subjective evaluation and enables more precise monitoring of rehabilitation outcomes, thereby improving the overall quality of care. Moreover, the integration of robotics with AI supports remote rehabilitation and telemonitoring, allowing patients to perform exercises in home settings while still receiving real-time guidance and supervision through connected systems. Another important aspect of robotic-assisted rehabilitation is its ability to enhance patient engagement and motivation through interactive and adaptive training environments, where patients receive immediate feedback and experience a sense of progress as the system adjusts to their capabilities. This not only improves adherence to rehabilitation programs but also accelerates recovery by ensuring consistent and correct exercise execution over extended periods. Additionally, robotic systems can simulate functional tasks and activities of daily living, enabling patients to practice meaningful movements that directly translate to improved functional independence [37].

MACHINE LEARNING FOR DIAGNOSIS AND MONITORING

Machine learning models are increasingly utilized for the early diagnosis and continuous monitoring of frozen shoulder by analyzing deviations in movement patterns, thereby providing objective, data-driven insights that enhance clinical decision-making and improve patient outcomes. Traditional diagnostic approaches for frozen shoulder often rely on subjective assessments, such as physical examination and patient-reported symptoms, which may lead to variability and delayed detection, whereas machine learning-based systems offer automated and consistent evaluation by processing quantitative movement data collected through wearable sensors. These systems analyze biomechanical parameters, such as joint angles, velocity, smoothness, and range of motion, to identify subtle abnormalities that distinguish pathological movements from normal shoulder function. A key strength of machine learning in this domain lies in its ability to recognize complex patterns within large datasets, enabling accurate classification of shoulder conditions based on movement characteristics, and models, such as support vector machines, random forests, and neural networks, are commonly employed to differentiate between healthy individuals and patients with frozen shoulder. Recent studies have demonstrated that inertial measurement unit (IMU)-based systems combined with machine learning algorithms can effectively classify shoulder tasks and identify functional impairments associated with frozen shoulder, achieving high levels of diagnostic accuracy and reliability. These systems extract both time-domain statistical features and kinematic features from sensor data, which capture essential aspects of movement quality, such as smoothness, coordination, and speed, thereby enabling precise characterization of patient performance. Figure 7 illustrates a classification model that differentiates between normal and pathological shoulder movements by following a structured workflow, where raw sensor data is first collected during functional tasks, then processed and analyzed using machine learning algorithms to generate diagnostic outputs that indicate the presence and severity of impairment. In this framework, feature extraction plays a crucial role by transforming raw signals into meaningful variables that can be used to train classification models, and these features include statistical measures, such as mean and variance as well as kinematic indicators, like spectral arc length and movement duration, which are particularly sensitive to abnormalities in motor control. The classification stage then applies trained models to categorize movements into normal or pathological classes, enabling automated detection of frozen shoulder and facilitating early diagnosis before severe functional limitations develop [38].

In addition to diagnosis, machine learning models are highly effective for continuous monitoring of disease progression, as they can track changes in movement patterns over time and provide quantitative feedback on patient improvement or deterioration, thereby supporting personalized rehabilitation planning and timely adjustment of treatment strategies. For instance, clustering algorithms, such as K-means, have been used to group different shoulder movement patterns based on range of motion, revealing distinct movement profiles that may correspond to varying stages or severity of musculoskeletal conditions. This ability to identify and monitor changes in movement patterns is particularly valuable in frozen shoulder, where progression occurs gradually and requires stage-specific interventions.

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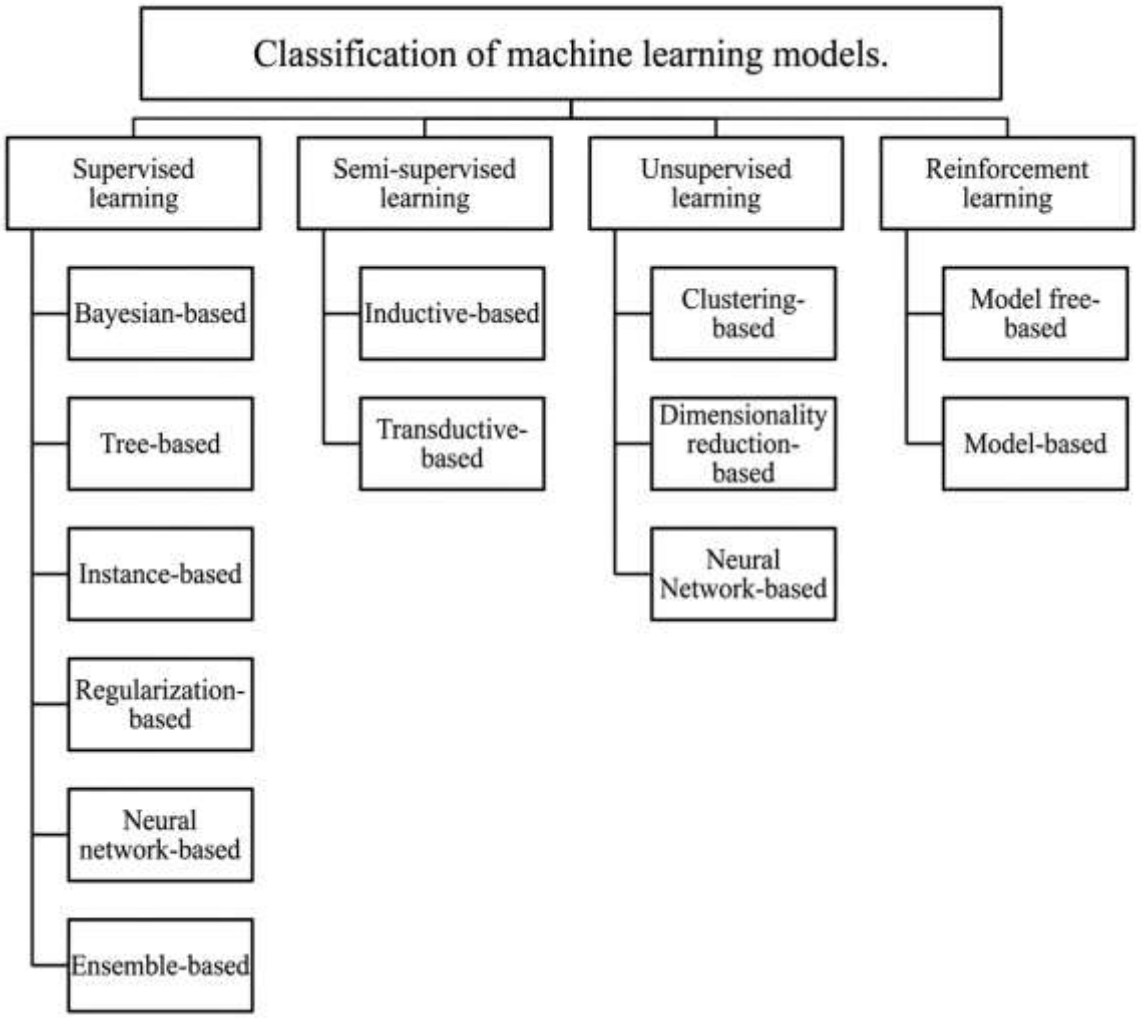


Figure 7. Machine learning model for movement classification.

Furthermore, machine learning models can be integrated with wearable and mobile technologies to enable remote monitoring and tele-rehabilitation, allowing clinicians to track patient performance outside clinical settings and ensure adherence to prescribed exercise programs. These systems can automatically detect deviations from correct movement patterns and provide alerts or recommendations, thereby enhancing patient engagement and improving overall rehabilitation outcomes. The combination of real-time data analysis and predictive modeling also enables early identification of potential complications, such as compensatory movements or reduced joint mobility, which can be addressed promptly to prevent further deterioration [39].

PERSONALIZED REHABILITATION THROUGH AI

AI-driven systems enable highly personalized rehabilitation by leveraging advanced data analytics and machine learning techniques to tailor therapy protocols according to individual patient characteristics, thereby improving treatment precision and effectiveness. Unlike traditional rehabilitation approaches that often follow standardized treatment plans, AI systems analyze large volumes of patient-specific data, including medical history, movement patterns, and physiological responses, to design customized interventions that align with the patient's unique needs and functional limitations. This personalization is particularly important in conditions, such as frozen shoulder, where variability in disease progression and patient response necessitates individualized rehabilitation strategies to achieve optimal outcomes. Continuous monitoring is a key feature of AI-driven rehabilitation systems, as it allows real-time tracking of patient performance through wearable sensors

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and digital platforms, enabling clinicians and algorithms to assess progress dynamically and make timely adjustments to therapy. These systems continuously collect and analyze data, such as joint angles, movement speed, and muscle activity, providing a comprehensive and objective evaluation of patient performance that goes beyond traditional intermittent assessments. The integration of real-time data processing enables AI algorithms to adapt therapy protocols instantly, modifying exercise intensity, duration, and complexity based on the patient's current condition and progress. Dynamic adjustment of therapy is one of the most significant advantages of AI-driven systems, as it ensures that rehabilitation remains responsive to the patient's evolving needs, thereby preventing undertraining or overexertion and optimizing recovery outcomes. For example, if a patient demonstrates improved range of motion and reduced pain, the system can increase exercise intensity or introduce more advanced movements, whereas signs of fatigue or improper execution can trigger a reduction in intensity or provision of corrective feedback. This adaptive approach not only enhances treatment effectiveness but also minimizes the risk of injury and ensures that therapy remains aligned with the patient's capabilities. Another important aspect of AI-driven rehabilitation is its ability to enhance patient engagement and adherence to therapy programs, as personalized and interactive systems provide continuous feedback, progress tracking, and motivation through digital interfaces such as mobile applications and virtual environments. Increased engagement is associated with better compliance and more consistent participation in rehabilitation exercises, which are critical factors for successful recovery. Additionally, AI systems can incorporate gamification elements and goal-oriented tasks to make rehabilitation more engaging and enjoyable, thereby improving long-term adherence and outcomes. Remote monitoring is also a key feature of AI-driven rehabilitation systems, allowing patients to perform exercises in home settings while maintaining continuous connection with healthcare providers, thereby improving accessibility and reducing the need for frequent hospital visits. This capability is particularly beneficial for patients in remote or underserved areas, as it ensures that high-quality rehabilitation services are accessible regardless of geographical constraints. AI-enabled tele-rehabilitation platforms can track patient progress, detect deviations from prescribed exercises, and provide real-time feedback, ensuring that therapy remains effective even outside clinical environments. Data analytics capabilities further enhance the effectiveness of AI-driven systems by enabling detailed analysis of patient performance over time, identifying trends, predicting outcomes, and supporting evidence-based decision-making. Machine learning models can analyze historical and real-time data to predict recovery trajectories, identify potential complications, and recommend adjustments to therapy plans, thereby facilitating proactive and preventive healthcare. This predictive capability allows clinicians to intervene early and modify treatment strategies before issues escalate, ultimately improving patient outcomes and reducing healthcare costs. Table 3 summarizes the key features of AI-driven rehabilitation systems, including real-time feedback, adaptability, remote monitoring, and data analytics capabilities, all of which contribute to a comprehensive and patient-centered approach to rehabilitation. Real-time feedback ensures immediate correction of movements, adaptability enables dynamic modification of therapy protocols, remote monitoring extends care beyond clinical settings, and data analytics provides actionable insights for continuous improvement of treatment strategies [40].

Table 3. Key features of AI-driven rehabilitation systems.

Feature	Description	Function in rehabilitation	Benefits
Real-Time Feedback	Provides immediate feedback based on patient performance	Detects errors and guides corrective movements instantly	Improves exercise accuracy and reduces risk of injury.
Adaptability	Adjusts therapy protocols based on patient progress	Modifies intensity, duration, and type of exercises dynamically	Enables personalized and progressive rehabilitation.
Remote Monitoring	Allows continuous tracking outside clinical settings	Uses wearable devices and mobile apps for home-based therapy	Increases accessibility and reduces hospital visits.
Data Analytics	Analyzes large volumes of patient data	Identifies patterns, tracks progress, and predicts outcomes	Supports evidence-based decision making.
Personalization	Customizes treatment plans for individual patients	Tailors exercises based on condition and recovery stage	Enhances effectiveness and patient satisfaction.

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Sensor Integration	Incorporates wearable and embedded sensors	Captures movement, posture, and muscle activity data	Enables objective and continuous monitoring.
AI-Based Decision Support	Uses machine learning algorithms for analysis	Assists clinicians in diagnosis and treatment planning	Improves clinical accuracy and efficiency.
Closed-Loop System	Continuous cycle of monitoring, analysis, and feedback	Adjusts therapy in real time based on performance	Ensures dynamic and responsive rehabilitation.
Tele-Rehabilitation	Enables virtual therapy sessions	Connects patients and clinicians remotely	Expands reach of healthcare services.
Progress Tracking	Records and visualizes patient improvement over time	Provides performance reports and insights	Enhances motivation and adherence.

VIRTUAL REALITY AND GAMIFIED REHABILITATION

Virtual reality (VR)-based rehabilitation systems have emerged as a powerful tool for enhancing patient motivation and engagement by creating immersive, interactive, and gamified therapeutic environments that transform traditional exercise routines into engaging experiences, thereby addressing one of the major challenges in rehabilitation, which is poor adherence to repetitive exercises. Unlike conventional physiotherapy, VR systems immerse patients in simulated environments where they can perform functional tasks and exercises in a visually stimulating and interactive manner, which not only reduces boredom but also improves emotional involvement and willingness to participate in therapy sessions. This increased engagement has been shown to positively influence rehabilitation outcomes, as patients are more likely to complete prescribed exercises consistently when they are presented in an enjoyable and motivating format. When integrated with artificial intelligence (AI) and sensor technologies, VR-based rehabilitation systems become even more effective by enabling real-time monitoring, adaptive feedback, and personalized exercise programs tailored to individual patient needs. Wearable sensors embedded within the system capture detailed movement data, such as joint angles, velocity, and coordination, which are continuously analyzed by AI algorithms to assess performance and detect deviations from correct movement patterns. This integration allows the system to provide immediate feedback to the patient through visual or auditory cues within the virtual environment, ensuring that exercises are performed accurately and safely. The combination of VR, AI, and sensors also enables the development of adaptive rehabilitation programs that adjust in real time based on patient performance, thereby ensuring that therapy remains challenging yet achievable, which is essential for maintaining motivation and promoting continuous improvement. For example, if a patient demonstrates improved range of motion or coordination, the system can increase the complexity or intensity of exercises, whereas signs of fatigue or incorrect movement can trigger modifications to reduce difficulty or provide additional guidance. This dynamic adaptability enhances the effectiveness of rehabilitation by aligning therapy with the patient's evolving capabilities and recovery stage. As depicted in Figure 8, a VR-based rehabilitation setup typically consists of a head-mounted display, motion tracking sensors, and an AI-driven software platform that together create a closed-loop system where patient movements are continuously monitored and analyzed, and corrective feedback is delivered instantly within the virtual environment. In such systems, patients perform guided exercises that are integrated into virtual scenarios, such as reaching, lifting, or interactive gaming tasks, which simulate real-life activities and enhance functional recovery. The immersive nature of VR allows patients to focus on the task rather than the effort, reducing perceived exertion and discomfort, which further contributes to improved adherence and performance. Clinical studies have demonstrated that VR-based rehabilitation can significantly improve outcomes, such as pain reduction, joint mobility, and quality of life in patients with musculoskeletal conditions, including frozen shoulder, by providing a structured yet engaging therapeutic environment that encourages consistent participation. Additionally, VR systems can incorporate elements of gamification, such as scoring, rewards, and progress tracking, which further enhance motivation and create a sense of achievement, thereby reinforcing positive behavior and sustained engagement in rehabilitation programs. Another important advantage of VR-based systems is their potential for remote rehabilitation or telerehabilitation, where patients can

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perform exercises at home while still being monitored and guided by AI-driven systems, thereby increasing accessibility and reducing the need for frequent clinical visits. This is particularly beneficial in situations where access to healthcare services is limited, as it ensures continuity of care and enables ongoing monitoring of patient progress.



Figure 8. VR-based AI rehabilitation system for shoulder therapy.

CHALLENGES IN IMPLEMENTATION

Despite their numerous advantages, AI-driven rehabilitation systems face several significant challenges that must be addressed to ensure their safe, effective, and widespread adoption in clinical practice, particularly in areas such as cost, technical complexity, data privacy, and system integration. One of the primary barriers is the high cost associated with developing, implementing, and maintaining AI-based rehabilitation technologies, including expenses related to advanced hardware, software infrastructure, data storage, and skilled personnel, which can limit accessibility, especially in low-resource healthcare settings. In addition, the technical complexity of these systems poses challenges for both clinicians and patients, as effective use requires specialized knowledge, training, and familiarity with digital technologies, thereby creating a learning curve that may hinder adoption and routine clinical use. Another critical concern is data privacy and security, as AI-driven systems rely heavily on large volumes of sensitive patient data, raising risks related to unauthorized access, data breaches, and misuse of personal health information, which necessitates strict regulatory compliance and robust cybersecurity measures. Ethical considerations further complicate the implementation of AI in rehabilitation, including issues related to informed consent, transparency, and potential bias in algorithms, which may lead to disparities in diagnosis or treatment if not carefully addressed. Moreover, ensuring patient trust is essential, as concerns about data confidentiality and the "black-box" nature of AI decision-making can reduce acceptance among both patients and healthcare providers. Integration with existing healthcare systems represents another major challenge, as many healthcare infrastructures are based on legacy systems that lack interoperability and standardized data formats, making it difficult to incorporate AI technologies seamlessly into clinical workflows. Fragmentation of healthcare data across different platforms and institutions further complicates this process, as inconsistent data formats and limited data sharing hinder the development and deployment of accurate and reliable AI models. Additionally, the absence of standardized protocols and frameworks for integrating AI into rehabilitation practice can lead to inefficiencies and variability in system performance. Ensuring the

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accuracy and reliability of AI models is also a critical issue, as these systems depend on high-quality, representative datasets for training, and limitations in data availability or quality can result in biased or inaccurate predictions that may negatively impact patient care. Furthermore, many AI systems are developed and tested in controlled environments, and their performance in real-world clinical settings may vary, highlighting the need for extensive validation and testing across diverse patient populations and healthcare contexts. The lack of explainability in AI models further complicates their clinical application, as healthcare professionals may be reluctant to rely on systems whose decision-making processes are not transparent or easily interpretable. Another important challenge is the need for continuous monitoring and updating of AI systems to ensure their effectiveness over time, as changes in patient populations, clinical practices, and data patterns may affect model performance, requiring ongoing maintenance and refinement. Additionally, regulatory and legal considerations play a significant role, as AI-driven rehabilitation systems must comply with healthcare regulations and standards, which can vary across regions and create additional barriers to implementation. The lack of clear regulatory guidelines in some areas may further delay adoption and create uncertainty among healthcare providers and developers. Despite these challenges, ongoing research and technological advancements are aimed at addressing these limitations through improved data standardization, enhanced cybersecurity measures, development of explainable AI models, and establishment of regulatory frameworks that support safe and effective integration of AI into healthcare systems. Collaborative efforts between clinicians, engineers, policymakers, and researchers are essential to overcome these barriers and ensure that AI-driven rehabilitation systems can be successfully implemented in real-world settings.

FUTURE DIRECTIONS

Future research in AI-driven rehabilitation systems should focus on enhancing sensor precision, as accurate data acquisition is fundamental for reliable assessment of patient movement and effective therapeutic interventions, and improvements in wearable sensor technology, including higher sensitivity inertial measurement units and advanced biosensors, will enable more precise tracking of joint kinematics and muscle activity, thereby improving the quality of input data used by AI models. Increasing sensor accuracy will also reduce noise and errors in data collection, which is essential for improving the performance of machine learning algorithms and ensuring consistent and reproducible outcomes in rehabilitation systems. At the same time, reducing the cost of these technologies is critical to ensure accessibility and scalability, particularly in low-resource settings where high implementation costs can limit adoption, and future innovations in low-cost hardware design and mass production techniques are expected to make AI-driven rehabilitation systems more affordable and widely available. Another important direction for future research is the integration of cloud-based and edge computing technologies, which can significantly enhance the efficiency, scalability, and responsiveness of rehabilitation systems, especially in remote and home-based settings. Cloud computing enables large-scale data storage, processing, and sharing, allowing clinicians to access patient data remotely and monitor progress over time, while edge computing facilitates real-time data processing closer to the data source, reducing latency and enabling immediate feedback during rehabilitation exercises. The combination of cloud and edge computing creates a hybrid architecture that balances computational efficiency and responsiveness, thereby supporting continuous monitoring and adaptive therapy in real-world environments. This integration is particularly beneficial for tele-rehabilitation, as it allows patients to perform exercises at home while receiving real-time guidance and supervision from AI-driven systems, thereby improving accessibility and continuity of care. Advancements in explainable artificial intelligence (XAI) represent another crucial area of research, as they aim to improve the transparency and interpretability of AI models used in rehabilitation systems, thereby increasing clinician trust and facilitating clinical adoption. Many current AI models, particularly deep learning algorithms, operate as “black boxes,” making it difficult for healthcare professionals to understand how decisions are made, which can limit their acceptance in clinical practice. Explainable AI techniques, such as feature importance analysis, visualization methods, and interpretable model architectures, can provide insights into the decision-making process of AI systems, enabling clinicians to validate and trust the outputs generated by these models. Furthermore, integrating explainable AI with rehabilitation

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systems can enhance clinical decision-making by providing clear and actionable insights into patient performance, such as identifying specific movement deviations or highlighting factors, contributing to poor outcomes, thereby enabling more targeted and effective interventions. This transparency not only improves clinician confidence but also supports patient engagement, as individuals are more likely to trust and adhere to therapy recommendations when they understand the rationale behind them.

CONCLUSION

AI-driven systems for real-time joint movement detection and correction represent a significant advancement in the rehabilitation of frozen shoulder by transforming traditional therapy into a more precise, efficient, and patient-centered approach. These systems integrate advanced sensor technologies, such as wearable motion sensors and muscle activity monitors, with intelligent algorithms capable of analyzing movement patterns in real time. This enables accurate tracking of joint mobility, early identification of abnormal or compensatory movements, and immediate corrective feedback, which is essential for improving exercise performance and preventing further complications. In addition, AI-driven rehabilitation allows for the development of personalized therapy programs tailored to the specific needs, progress, and limitations of each patient. Continuous monitoring ensures that treatment protocols can be dynamically adjusted based on real-time data, thereby enhancing the effectiveness of interventions and promoting faster recovery. These systems also improve patient engagement by providing interactive feedback and progress tracking, which encourages adherence to rehabilitation programs. Overall, AI-driven technologies have the potential to significantly improve clinical outcomes in frozen shoulder rehabilitation. Continued innovation and refinement will be essential to address existing challenges and ensure their successful integration into routine clinical practice.

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