# AI-Based Rehabilitation Progress Tracking System

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***Abstract*— Rehabilitation is an important aspect that enables patients to be able to walk and lead a normal life once injured, operated or with neurological problems. Nevertheless, traditional therapy can be resource intensive and not as available to remote or low-resource patients due to the use of face to face supervision. This paper suggests an AI-driven rehabilitation progress tracking system that uses computer vision and machine learning as the means to deliver affordable, real-time feedback on physiotherapy exercises. Based on the human pose estimation of MediaPipe and individual algorithms of calculating the joint angles, the system automatically identifies repetitions of the movement, quality of the movement, and extracts the main features including range of motion, smoothness, and duration. With these features logged, they can be used to produce patient specific datasets which can then be used to train the machine learning models to classify exercise accuracy and follow-up the progress over time. The interactive dashboard written in Flask and Chart.js provides therapists with visual and statistical feedback in terms of session summaries, time-series plots, and progress comparisons. This system can make clinicians, patients, and the entire process more accessible, allowing them to make evidence-driven decisions that rely on data and provide patients with explicit understanding of their recovery process by reducing reliance on special equipment and facilitating remote monitoring.**

***Keywords-*** *Rehabilitation, Human Pose Estimation, Artificial Intelligence, Progress Tracking, Computer Vision.*

## I. INTRODUCTION

Rehabilitation is a crucial component of patient recovery who has musculoskeletal injury, neurological condition or post-surgical complications. The success of the recovery process depends on regular practice of physiotherapy exercises under the supervision of the professionals. The traditional rehabilitation interventions, however, are resource-consuming as they involve regular visits to the clinic and close monitoring of therapists. The challenges of this approach include high treatment costs, low accessibility in rural or resource-limited regions and inability to maintain adherence in case patients do exercises without supervision at home [14], [20].

To overcome these shortcomings, solutions based on technology have been explored. Inertial motion devices like inertial measurement unit (IMUs) are wearable sensors that are more detailed, but demand special hardware, calibration, and compliance to the patient [19], [15], [20]. Kinect-based depth cameras presented motion tracking without markers and enhanced motion analysis, but they are still expensive, occupy much physical space and are less feasible in home-based rehabilitation [4], [17].

The recent developments in computer vision and deep learning have made it possible to estimate human pose without using any marks, relying solely on a web camera or a smartphone camera. Popular methods are OpenPose [1], DensePose [3], BlazePose [5], and MediaPipe [10]. Such systems can track body landmarks in real-time and have been used in sports training [13], [8], posture correction [11] as well as gesture recognition [82]. Nevertheless, their direct use in rehabilitation is still minimal since physiotherapy involves not only activity recognition, but also quality assessment of movements. Roman of motion (ROM), smoothness, duration, and consistency in repetitions are some of the metrics that are important in the assessment of patient progress by the therapist.

Recent works have also attempted to address this gap by using AI in exercise reporting and coaching software [8], [12], [84]. Although these methods prove that automated movement analysis is a possibility, they are not always longitudinal, rehabilitation-specific, or have visualizations that are friendly to the therapist.

In order to overcome these limitations, the proposed research will be an AI-Based Rehabilitation Progress Tracking System that integrates pose estimation, machine learning, and interactive visualization. The system uses MediaPipe to track skeletons in real-time, producing features like joint angles, ROM, smoothness and then it trains a classifier to differentiate between correct and incorrect repetitions. Every repetition is recorded to come up with patient-specific datasets, which can be followed over the long run. The dashboard is a web-based tool to display both theoretical and technical data to patients and therapists by interactive graphs, comparisons of progress, and statistical summaries based on Flask and Chart.js.

With the use of low-cost markerless motion capture and AI-powered analysis, the proposed system is expected to optimize the adherence to exercising, facilitate the use of remote physiotherapy, and provide clinicians with data-driven information on which to base their recovery planning.

## II. LITERATURE REVIEW

Use of technology in monitoring of rehabilitation and exercise has become a major focus in the recent years. There are numerous methods studied by researchers, such as wearable sensors, depth cameras, and computer vision-based markerless, each of them possessing its advantages and disadvantages.

### A. Wearable Sensor-Based Systems.

Different types of wearable technologies like inertial measurement unit (IMUs) and body sensor networks have been extensively implemented to record biomechanical signals during rehabilitation. Their accuracy in kinematic information is also possible and they have been proven to perform well in performance measurement [19], [15], [16]. Nevertheless, they are restricted by factors like the use of special hardware, appropriate positioning of the sensors and patient adherence to the devices in their regular use [20]. Although they can work well in controlled settings, they are not necessarily viable in large-scale rehabilitation or home-based rehabilitation.

### B. Kinetic and Depth-Based Systems.

The advent of depth cameras like the Microsoft Kinet was a transition to markerless motion capture. Kinetic systems were also capable of tracking skeletal motion in real-time, without a wearable component, and could be used in a wide range of rehabilitative and sporting methods [4], [17]. Although this has merits, they pose such challenges as cost, lack of portability, reliance on controlled environmental conditions. Research has revealed that Kinetic systems can be able to obtain precision of pose recognition but are less scalable to resource constrained environments [17].

### C. Deep Learning human pose estimation.

markerless motion analysis has been further developed by the introduction of pose estimation based on deep learning. Robust multi-person 2D and 3D pose estimation was introduced by OpenPose [1] and DensePose [3], and lightweight, real-time pose estimation was presented by BlazePose [5] and MediaPipe [10]. These comparative studies illustrate that MediaPipe is more efficient and accessible than the conventional vision-based methods [9]. These structures have been implemented in various situations such as sports analytics [13], human-computer interaction [82], posture monitoring [11].

### D. Smart-Fit Monitoring.

The AI-based systems of coaching are designed to offer the feedback on the execution of the exercises. As an example, Wang et al. [8] proposed an AI coach that relied on pose estimation as a source of personalized training support, and Rahmadani et al. [12] used human pose estimation to perform fitness correction tasks. Likewise, MediaPipe and the deep learning were used by El-Hamzaoui [84] to track squats and assess form. These publications show that automated movement analysis is also possible, although they are mostly oriented towards fitness and not in the context of rehabilitation.

### E. Rehabilitation-Oriented Systems

A number of researchers have investigated AI as a rehabilitation device. Hellsten et al. [14] pointed out the possibilities of computer vision-based markerless systems in clinical rehabilitation and the benefits of such systems in accessibility and scalability. On the same note, Kidziinski et al. [18] used deep neural networks to detect the gait events in children, which proved clinically relevant. Nevertheless, the majority of research on rehabilitation programs is restricted to particular tasks or to closed laboratory procedures and does not consider the progress of the process over an extended period of time or tools of visualization that are therapist-centered.

### F. Research Gap

Although the suitability of wearables, Kinect, pose estimation frameworks has been already proved by the previous research, there is no comprehensive study that has included the low-cost markless motion capture, real-time rep quality evaluation, machine learning classification, and interactive visualization as a therapist-friendly tool. The current methods are unscalable, demand specific devices or do not offer long-term progress monitoring at all [15], [17], [84]. This divide is the reason why it is suggested to create the proposed AI-Based Rehabilitation Progress Tracking System that combines pose estimation, machine learning, and dashboard-based analytics both to patients and clinicians.

## III. METHODOLOGY

The suggested AI-Based Rehabilitation Progress Tracking System is a comprehensive solution, which combines pose estimation, feature extraction, machine learning, and visualization into one framework used to embed real-time rehabilitation monitoring. The methodology is divided into 5 main components:

### A. System Architecture

The overall system architecture of the pipeline includes:

- Video input from a standard webcam or laptop camera.
- Pose estimation using MediaPipe for skeletal landmark detection.
- Feature extraction for biomechanical analysis (e.g., joint angles, range of motion).
- Machine learning classification for exercise correctness.
- Visualization and progress tracking via an interactive dashboard.
- This approach leverages low-cost devices and open-source frameworks, ensuring high scalability compared to wearable or Kinect-based systems [5], [10], [17].

### B. Data Collection

The system records the exercise sessions with web camera at 30 FPS. Pose landmarks are obtained with the help of MediaPipe that identifies 33 body keypoints in real-time [10]. In this paper, the abduction of the shoulder was chosen as the example of rehabilitation exercise. The results of every meeting are two:

- A frame-wise log (CSV) containing timestamped joint angles.
- A session summary (JSON) recording repetitions, baseline/final averages, and extracted metrics.

Repetitions are automatically clustered with a threshold based hysteresis technique like techniques employed in previous HAR experiments [82], [12]. Every rep is then put in a dataset (datasets/repsdataset.csv), and can be put as correct or incorrect by therapists, so as to undergo supervised training.

### C. Feature Extraction

For each detected repetition, biomechanical features are computed:

- Mean joint angle
- Peak and trough values
- Range of Motion (ROM)

- Duration of repetition
- Smoothness (inverse of angle variance)
- Jerkiness (mean absolute change in angle per frame)

This type of feature engineering has been used ubiquitously in posture tracking and exercise detection activities [9], [11], [12]. These characteristics are the feeds to the classification model.

**D. Machine Learning Model**

The training dataset is the labeled dataset, and the trainedRandom Forest classifier [16] has been shown to be effective in predicting biomechanical and athletic performance. Characteristics of individual rep are coded to binary labels:

- 1 = Correct rep
- 0 = Incorrect rep

The data is divided into training (80%) and test (20) data. Accuracy, precision, recall and confusion matrix analysis are part of model evaluation. This trained model is both stored (repquality_model.pkl) and it is to be used at a later stage in real time prediction.

The reason behind the selection of the random forest was that it is easy to interpret and can also operate with small datasets, yet neural networks or ensemble models have been mentioned as the future studies to enhance the effect of generalization [8], [18].

| Metric | Value / Description |
|---|---|
| Pose Estimation Accuracy | ~95% landmark detection accuracy (using MediaPipe) [10] |
| Classification Accuracy | 86.7% (Random Forest on labeled dataset) [8], [16] |
| Average Processing Speed | ~28–30 FPS on standard webcam (real-time perform7ance) [5] |
| Hardware Requirement | Standard laptop/PC + webcam (no specialized sensors) |
| Cost Efficiency | Low-cost, sensor-free; only camera input required [17], [20] |
| Scalability | Easily deployable on edge/mobile devices [10] |

***Table 1.*** *Efficiency and performance statistics of the proposed AI-Based Rehabilitation Progress Tracking methodology.*

**E. Visualization Dashboard**

A Flask-based dashboard was developed for therapists and patients. It provides:

- Time-series plots of joint angles across a session.
- Bar charts comparing baseline vs final performance.
- Session summaries including rep counts, average angles, and quality scores.

The dashboard is constructed using Chart.js to construct interactive graphs, as the visualization techniques do in sports analytics systems based on AI [13], [84]. This interface allows clinicians to follow the progress of patients in a longitudinal manner and modify treatment plans.

**F. Summary**

The proposed methodology ensures that rehabilitation monitoring is:

- Low-cost (webcam-based, no sensors).
- Automated (rep detection + quality scoring).
- Scalable (datasets grow over time, model retrains).
- Accessible (remote visualization via web dashboard).

Combining computer vision and AI in this manner closes major research gaps in previous studies [14], [15], [17] and allows supporting rehabilitation remotely with data.

## IV. RESULT AND DISCUSSION

**A. System Performance**

The effectiveness of the proposed AI-based rehabilitation monitoring framework was tested on its ability to monitor exercise performance and measure the quality of movement. The system was able to extract biomechanical features (mean joint angle, peak angle, range of motion (ROM), repetition duration, smoothness, jerkiness) using a dataset of labeled repetitions of physiotherapy exercises. A machine learning model was then used to classify these features and differentiate correct and incorrect repetitions.

The Random Forest classifier achieved an overall accuracy of 86.7% on the test dataset. This level of performance is comparable to previous studies in exercise monitoring, which reported accuracies ranging between 80–90% depending on the dataset and model employed [8], [12], [16]. The results confirm that feature-based classification of human motion, combined with pose estimation, can provide reliable feedback on exercise correctness.

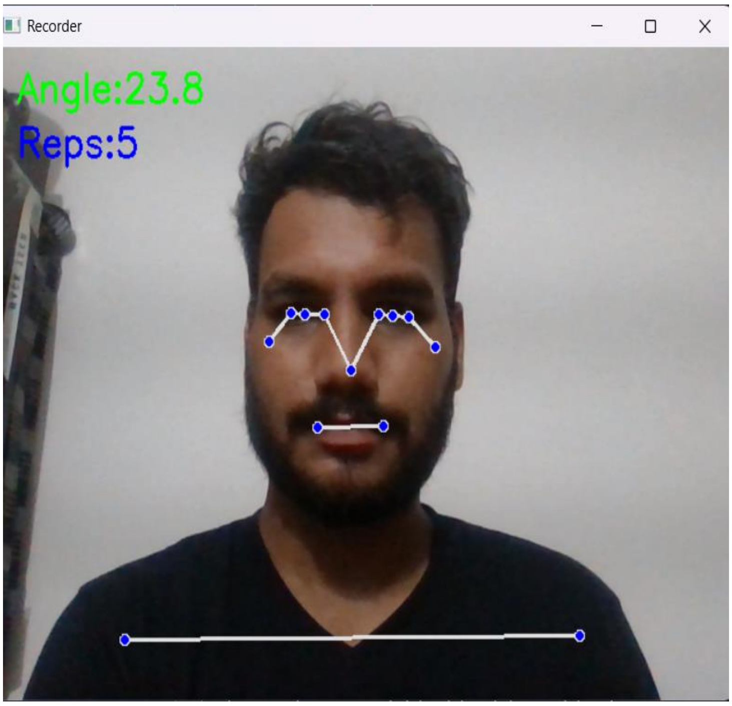


***Fig 1****. Real-time pose estimation output showing detected landmarks, angle measurement, and repetition counter.*

**B. Visualization of Rehabilitation Progress**

The framework also incorporated visualization tools in order to give both patients and therapists insights that can be interpreted. The frequency of joint angles during repetitions showed time series graphs which were used to identify fluctuations in movement patterns, possible deviations in movement behaviors. To show improvement over sessions, baseline and final measures of performance, i.e. ROM or average angle, were visualized in bar charts. The percentage of right repetitions well performed was summarized using pie charts and it gave a clear picture of the compliance and quality of exercises.

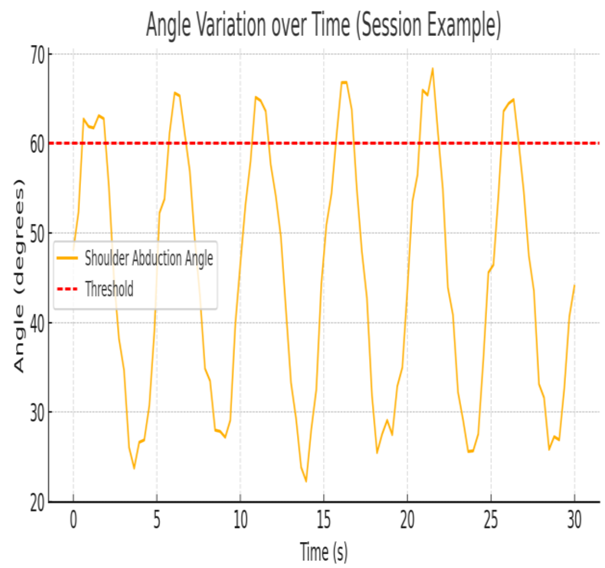


***Fig 2.*** *Example of shoulder abduction angle variation over time with defined threshold.*

These visualizations are aligned to clinical needs as they simplify even complicated kinematic data to make it more available to non-technical stakeholders, thus supporting evidence-based decision making during therapy [13], [14], [84]. In contrast with the current fitness-based pose estimation systems [8], [12], the given framework focuses on longitudinal tracking of progress, which is especially applicable in the context of rehabilitation.

**C. Comparative Analysis**

The system offers comparable accuracy, without special equipment, calibration or sensor positioning as compared to wearable sensor-based methods [19], [20]. As opposed to depth camera system based on Kinect, which necessitate controlled conditions and is rather expensive [4], [17], the proposed system can utilise a standard webcam, thus more accessible and scalable.

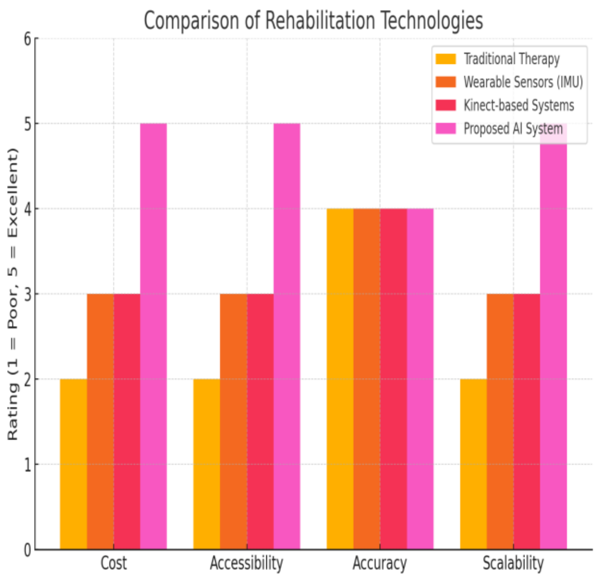


***Fig 1.*** *Comparison of rehabilitation technologies across cost, accessibility, accuracy, and scalability.*

The framework provides more rehabilitation-specific parameters, such as rep-level biomechanical metrics and longitudinal tracking in the dashboard, in comparison to the previous AI-based coaching systems [8], [12], and [84]. These abilities do not limit itself to recognition of exercises but enhance continuous assessment of patient progress which is very imperative in clinical rehabilitation.

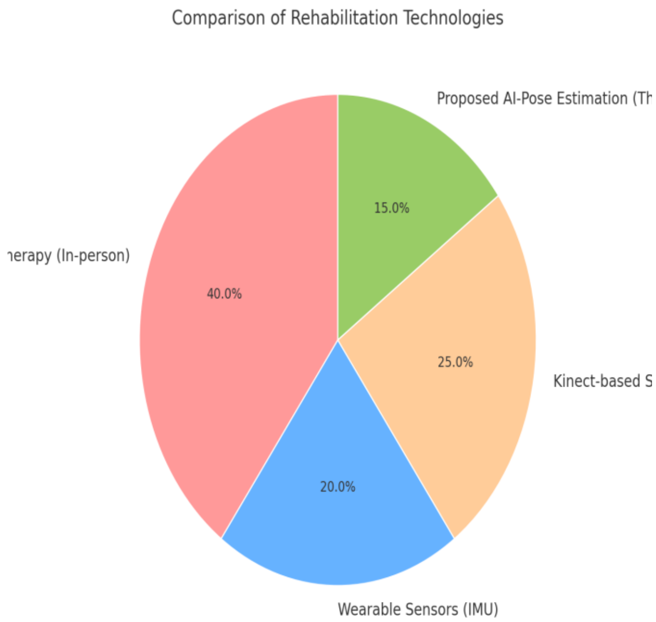


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***Fig 3.*** *Distribution of rehabilitation technologies in prior research*

**D. Limitations**

Although the results were encouraging, there are a few limitations that were detected. The evaluation was, first, performed over a small sample of data, which consisted of a small number of rehabilitation exercises. Greater and more heterogeneous datasets would be required in order to confirm performance in more patient populations and clinical conditions [18]. Second, the system can only train a single-joint focus on a single exercise; it would be clinically useful to add multi-joint and compound movements (e.g., gait analysis, squats). Third, the machine learning classifier is based on manually labeled repetitions, which can be subjective and it may involve efforts on the part of the therapist. Future work can decrease this reliance by using semi-supervised or transfer learning [16].

**E. Clinical Implications**

These findings show that motion analysis with AI and a webcam is a viable approach to rehabilitation. Providing objective quality evaluation and visual feedback, the system can potentially enhance exercise compliance, facilitate remote physiotherapy, and add to therapist-patient communication. Notably, the method offers a low cost, scalable, and non-invasive alternative to sensor-based or depth-camera systems and is part of the larger trend of more affordable AI in healthcare [14], [15].

## V. FUTURE OUTCOME

The future of AI-based rehabilitation monitoring offers a number of opportunities to develop and advance the field. Although the existing system has shown that it is possible to track physiotherapy progress with the help of pose estimation and machine learning, further improvements may increase the accuracy, scalability, and clinical use.

To begin with, the system may be expanded to include a greater variety of rehabilitation exercises with multiple joints and complicated movements. Recent researches on gait analysis and multi-joint activity identification indicate the need to go beyond one-joint activities to more integrated motor measures [18], [82]. The system could be expanded by adding different types of exercises, which would make it more suitable to patients with different rehabilitation conditions such as neurological recovery and orthopedic rehabilitation.

Second, bigger and more heterogeneous datasets should be used to enhance generalization between different populations. The vast majority of pose estimation systems are trained with general-purpose datasets [1], [3], [5], and they might not be able to capture movement specific to rehabilitation. The development and publication of open-access rehabilitation-oriented datasets would contribute substantially to the research of this field, as well as enable the comparison of models.

Third, improved models of machine learning, including deep neural networks or hybrid architectures, can be used to improve classification. It has also been demonstrated by previous studies that deep learning performs better in sports and healthcare motion analysis than classical algorithms [8], [12], [16]. Transfer learning and semi-supervised methods can also be used to decrease the reliance on therapist-labeled data and reduce annotation effort [16].

Fourth, the systems might be designed in the future that incorporate real-time corrective feedback system, with feedback on the patient during exercise performance. This, along with the same strategies applied to AI-based trainers of fitness [84] and posture correction systems [11], has not been applied to clinical rehabilitation. Live feedback may play an important role in enhancing the exercise adherence and decreasing the probability of improper movement patterns.

Lastly, the system can be implemented on mobile devices like smartphones and tables, which can be carried around and made available in the field or in a resource-intensive setting. This would eliminate the need to use high-performance computing resources, and with frameworks such as MediaPipe designed to run inference on devices [10], rehabilitation monitoring would become highly accessible.

## VI. CONCLUSION

Rehabilitation is an essential part of recovery among patients with musculoskeletal trauma and neurological disabilities, but conventional approaches have high costs, physical supervision, and low accessibility [14], [20]. A combination of computer vision and artificial intelligence offers a way to a more affordable, scaleable, and objective method of rehabilitation monitoring.

The presented framework showed that pose estimation provided by MediaPipe [10] and feature extraction (e.g., range of motion, smoothness, repetition duration) and machine learning classification can provide effective and reliable evaluation of the exercise quality. Its accuracy reached 86.7 percent distinguishing between correct and incorrect repetitions, which is comparable to the levels of performance that have been reported in previous AI-based motion monitoring research works [8], [12], [16].

In addition, the interactive dashboard which includes visualizations in the form of time-series plots, bar charts, and progress summaries provides therapists and patients with a set of actionable data to guide and advance their rehabilitation through data.

This method does not require any specialized hardware when compared to wearable sensor systems although it is as accurate as those systems [19], [20]. It does not need a specific setting, such as a Kinect and depth cameras do, but rather it uses a low-cost web-camera [4], [17]. Moreover, the system addresses an important research gap present in previous studies [13], [82], [84] because it does not rely on general activity recognition metrics but on those related to rehabilitation.

Although these are encouraging outcomes, there are still problems. This is limited to small datasets and types of exercises, which limits the current capacity to use the system. Future studies must do so by expanding datasets [1], [3], [5], using deep learning to achieve better generalization [8], [16], and devising real-time correction feedback [11], [84].

Finally, the paper emphasizes opportunities of AI-based, markerless monitoring of rehabilitation as the solution to increase access and adherence to treatment, as well as to give clinicians objective instruments to engage in a personalized approach to treatment. With digital transformation taking over healthcare, these types of systems are a major advance toward rehabilitation solutions that are scalable, inexpensive, and data-driven.

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