A Proposal for a Mobile Application Pipeline for Posture-Based Muscle Rehabilitation at Home

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***Abstract*—This work outlines the development process of a rehabilitation system from smartphones to provide remote monitoring and real-time feedback assistance in muscle rehabilitation exercises. The system leverages advanced machine learning techniques, such as pose estimation techniques and anomaly detection models, in tracking users' movements and assessing the performance of exercises. The system is designed to identify deviations from correct movement patterns and provide corrective feedback, allowing patients to engage in home-based rehabilitation without specialized hardware. This paper details the system design, data acquisition methods, and the machine learning models used to detect incorrect movements. The outlined pipeline is intended to facilitate the creation of an affordable, cost-effective, and scalable rehabilitation platform for strengthening patient adherence to exercises and optimizing recovery outcomes.**

***Index Terms*—Digital health technology, Tele-rehabilitation, Pose estimation, Home-based rehabilitation**

I. Introduction

Digital health technology has revolutionized the field of rehabilitation by introducing innovative solutions that enhance patient care and recovery outcomes. The integration of digital tools in rehabilitation aims to address the challenges associated with traditional therapy methods, such as accessibility, cost, and patient adherence [1]. Among the most common conditions requiring rehabilitation are muscle injuries, affecting millions of individuals worldwide each year [2]. These injuries can result from various causes, including sports-related activities, occupational hazards, or age-related degeneration. Recovery from muscle injuries often necessitates prolonged and supervised therapy sessions to ensure proper healing, restore mobility, and prevent future complications. However, conventional rehabilitation programs can be demanding, requiring patients to make frequent visits to healthcare facilities, which may not always be feasible due to geographical, financial, or logistical constraints. As a result, there is a growing need for innovative rehabilitation strategies that improve patient engagement, provide personalized care, and enhance treatment outcomes [3].

Traditional approaches methods can be restrictive and inconvenient, particularly for patients who need continuous care and personalized feedback. In response to these challenges, tele-rehabilitation rises as a new method of rehabilitation, allowing patients to do rehabilitation session remotely, such as at home, reducing hospitalization times and costs [4]. One of the key elements that enhance the effectiveness of tele-rehabilitation is with the help of serious games, who has proven to be effective in the engagement of the patient and also, its entertainment. Unlike conventional games, who purpose is for fun, serious games have a principal educational role or rehabilitation purposes, providing engagement and immersive experiences to capture the player's attention and motivate consistent practice [5].

Moreover, with the growing demand for remote and digital fitness solutions, intelligent training platforms provide a viable alternative to gym-based training routines. The COVID-19 pandemic has accelerated the rate of adoption of training routines at home, highlighting the need for adaptive and data-intensive fitness solutions [6], [7]. The proposed system here adheres to this trend by laying out an interactive and responsive system that has the potential to serve novice as well as advanced users in achieving their health and fitness objectives without human intervention on a ongoing basis.

II. Related Work

Recent advances in non-contact technologies for monitoring physical exercise, particularly those involving computer vision and image processing, are extremely relevant to the development of serious games for posture-based muscle rehabilitation. For instance, Khanal et al. review [8], highlights the use of technologies like Microsoft Kinect and infrared cameras to monitor key physiological parameters such as heart rate, respiratory rate, and body temperature during exercise, without the need for wearable devices. Debnath [9], also conducted a review in this scope to provide an in-depth survey of vision-based techniques used to monitor and support physical rehabilitation. The study concludes with future research directions, emphasizing the need for personalized rehabilitation models and improved real-time feedback systems, to enhance accessibility and effectiveness for both patients and healthcare providers.

Benettazzo et al. [10] developed a low-cost vision-based rehabilitation system using a Microsoft Kinect camera and open-source software to track key body joints, employing Artificial Neural Networks (ANNs) for exercise classification to provide feedback on movement accuracy and help users correct posture in future sessions. Nowadays, skeleton extraction for estimating human pose and movements relies on advanced 2D and 3D pose estimation models, which enable accurate motion tracking. Aguilar Ortega et al. [11] evaluated state-of-the-art 2D and 3D pose estimation models for tracking limb movements across various body positions and camera angles. They found that while 3D methods provide more detailed motion tracking, 2D methods, particularly AlphaPose, offer sufficient accuracy for estimating joint angles, making them a practical and cost-effective solution for rehabilitation monitoring. This context has also been extended to smartphone-based rehabilitation systems, for example using MediaPipe for pose estimation, providing movement quality assessment and feedback as an affordable, accessible alternative to traditional rehabilitation with remote monitoring and personalized exercise programs [12]. However, outside the rehabilitation context, Kaldarova et al. [13] introduced an AI-driven personal coaching system for deadlift training that utilizes PoseNet for skeletal analysis and a deep learning model to classify repetition correctness, providing real-time feedback to improve form, reduce injury risk. If desired, the classification of these actions can be performed by evaluating the extracted skeleton in each frame and analyzing the sequence using a sequential network [14]. For instance, Zaher et al. [15] conducted a comparative analysis of multiple models, including LSTM, BiLSTM, CNN, and CNN-LSTM, highlighting their respective strengths and weaknesses in classifying physical rehabilitation exercises.

In addition to posture-based rehabilitation and exercise classification, researchers have also explored solutions to address muscle weakness, particularly in response to the challenges posed by COVID-19 lockdowns and reduced physical activity. Aiming to combat muscle weakness in older adults, exacerbated by COVID-19 lockdowns and inactivity Carraro et al. [16] proposed a study that involved series of simple, easy-to-learn exercises that can be performed in bed, targeting the 400 skeletal muscles essential for everyday activities. It's a practical, home-based solution that can maintain independence and quality of life for frail older adults. These type of solutions were highly investigated during the pandemic [17], [18], but have also been expanded into the scope of telerehabilitation [19], inspired by the impossibility of in-person rehabilitation.

The use of robots for rehabilitation is an intriguing approach to muscle rehabilitation, with systems like Robot Gym [20] offering a cost-effective and labor-efficient alternative that enables therapists to treat up to six patients simultaneously, compared to traditional one-on-one therapy sessions. This type of approach has a higher initial cost, but it can result in long-term savings by increasing therapist productivity. Although promising, Robot Gym did not prove to be as effective as traditional therapy, but it is still a viable option for low-resource settings, offering an affordable and scalable solution for stroke rehabilitation.

III. System Design and Pipeline

The development of an effective home rehabilitation system requires a well-structured pipeline that ensures accurate movement tracking, real-time feedback, and anomaly detection for exercise correction. This section describes the proposed smartphone application's architecture, delineating its fundamental components including data acquisition, pose estimation, feature extraction, and anomaly detection (Figure 1). With the utilization of advanced machine learning techniques, the system is designed to identify incorrect movements based on a dataset of well-performed exercises and provide users with real-time corrective feedback. The goal is to create an user-friendly and accessible solution for effective and safe rehabilitation exercise performance without the necessity for specialized hardware except for a smartphone. By enabling users to get immediate guidance without the need for wearables or external sensors, this system has the potential to make home rehabilitation more convenient, scalable, and accessible to everyone.

Fig. 1. System pipeline for the mobile rehabilitation app, showing the stages from video input and pose estimation to feature extraction, anomaly detection, and real-time feedback based on movement patterns, speed, angles, and symmetry.

One of the most important components of the proposed system is the dataset that will be employed to train the anomaly detection model as well as accommodate proper movement correction. The dataset must include a diverse set of well-performed exercise executions to establish a baseline for correct movements. It will encompass a selection of rehabilitation and gym exercises commonly prescribed for motor rehabilitation, chosen for their role in improving mobility, strength, and coordination. These include lower-body exercises such as squats, lunges, and step-ups, which are essential for strengthening leg muscles and improving balance; upper-body exercises like shoulder raises, bicep curls, and arm extensions, targeting mobility and muscle control; core stabilization exercises such as planks, seated leg lifts, and pelvic tilts, which play a crucial role in maintaining posture and preventing injuries; and functional movement exercises like sit-to-stand transitions and gait training movements, aimed at improving real-life mobility. By covering a broad spectrum of exercises across different muscle groups, the dataset will help the system generalize better to various rehabilitation needs. Pose estimation plays a fundamental role in tracking these exercises, with algorithms like MediaPipe [21] and OpenPose [22] extracting skeletal data from real-time video input, allowing the system to analyze joint positions and movement trajectories. These algorithms detect and track key body joints, providing a structured representation of posture and movement, which is essential for ensuring accurate feedback.

Once pose estimation data is collected, the system will proceed to feature extraction, where key biomechanical metrics will be calculated to assess the accuracy of exercise execution. These include joint angles, movement patterns, speed, and symmetry, all of which are important in determining whether the exercise is performed correctly. Joint angles are measured to keep the user's range of motion in an effective and safe range so that the rehab exercises are executed according to prescription. Movement patterns, which track the trajectory of key joints over time, will be analyzed to detect any deviations from the expected path, identifying improper form or uncoordinated movements. Speed analysis will also be performed to ensure exercises are performed at an optimum speed; too quickly can lead to injury, and too slowly can lead to a reduction in the effectiveness of the exercise. Symmetry detection will be required for the provision of balanced movement, especially for exercises that incorporate both sides of the body, such as squats or lunges. By capturing these essential features, the system can determine if the movements of the user are in accordance with rehabilitation standards, thus assisting in the detection of erroneous executions for correction.

To detect anomalies in exercise execution, the system will incorporate an unsupervised anomaly detection model that does not rely on extensive labeled datasets. Techniques like Autoencoders and Isolation Forest will be employed to identify incorrect movements by comparing real-time execution data to the learned baseline of correctly performed exercises [23], [24]. Autoencoders will be used to learn to reconstruct successfully performed movements' patterns and any deviation from such reconstruction as abnormal. This allows the system to label faulty movements without labeling each deviation separately, making it able to learn from new subjects and drills. Isolation Forest, a tree-based system, will be used to find outliers by isolating abnormal movement patterns, such as random joint angles or abnormal speed. By applying these models, the system can detect deviations reliably in real-time and provide instant feedback to the users to rectify the incorrect motions. The unsupervised approach ensures that the system can generalize across a variety of exercises, body shapes, and movement patterns and yet remain effective in real-world applications.

The feedback mechanism is one of the central elements in the system that provides users with instantaneous corrections to assist them in refining their form in rehabilitation exercises. Once an anomaly is detected, the system will provide corrective feedback through visual, auditory, or haptic feedback, based on the preferences of the user and the features of the device. For example, users receive visual feedback in the form of color-coded skeleton overlays, where poorly aligned joints are red or yellow to indicate areas that need realignment. On-screen cues may provide explicit suggestions, such as ”Lower your knees more” or ”Align the shoulders with hips.” The system can also use voice-guided feedback to provide hands-free corrections, which would be especially helpful for users who are focusing on their movement. Besides real-time correction, the app will also give users a report on their performance after each session, including most frequent mistakes, improvement made, and where they need to improve further. This constant feedback loop will not only avoid accidents for the users but also allow them to track rehabilitation advancements over time, thereby home rehabilitation being maximized for efficacy and effectiveness.

IV. Mobile Deployment of AI Models

Model running software refers to software programs or libraries that are designed to load, interpret, and run machine learning models on specific devices, such as computers, mobile devices, embedded systems, and more. These software are essential for deploying machine learning (ML) models in production environments, where models need to be run in real-time or on devices with limited computing resources. They handle tasks such as inference, where models are used to make predictions or make decisions based on the input data.

TensorFlow Lite is an optimized version of the TensorFlow framework [25] designed for mobile devices and embedded systems. It enhances performance by reducing model size and computational demands, making it ideal for resource-constrained devices. Additionally, TensorFlow Lite supports hardware acceleration on compatible devices, utilizing GPUs and specialized machine learning processors to improve efficiency. Its seamless integration with Android, iOS, and other platforms simplifies deployment in mobile applications. The framework offers flexibility by supporting various machine learning models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs). Furthermore, TensorFlow provides conversion tools that allow trained models in the standard TensorFlow framework to be efficiently transformed into the TensorFlow Lite format, enabling their use in lightweight and real-time applications.

PyTorch Mobile is an extension of the PyTorch framework [26] that enables the execution of machine learning models on mobile devices. It provides a flexible and straightforward way to deploy PyTorch models on smartphones and other portable devices. With direct integration into PyTorch, trained models can be easily converted and executed on mobile platforms using PyTorch Mobile, ensuring a seamless transition from development to deployment. PyTorch is known for its flexibility and expressiveness, featuring a user-friendly syntax and dynamic nature that facilitate the development and experimentation of complex models. Additionally, it benefits from a growing and active community, providing a wealth of resources, tutorials, and examples to assist developers in leveraging PyTorch Mobile effectively. Both TensorFlow Lite and PyTorch Mobile are powerful tools for deploying machine learning models on mobile devices, offering efficiency, performance, and flexibility for a wide range of applications.

Although TensorFlow Lite and PyTorch Mobile provide tools for running ML models on edge devices, the use of Autoencoders and Isolation Forests adds computational complexity. Autoencoders, particularly deep architectures, and Isolation Forests with a large number of trees can be computationally expensive to infer. On resource-constrained mobile devices, this can lead to increased latency or thermal throttling, which is a problem that should be addressed [27].

The development of the application began with a focus on creating a user-friendly and responsive interface using technologies compatible with the Android platform. The application's architecture was designed to integrate the computer vision algorithm, ensuring that the movement recognition results are presented to the user in a clear and intuitive manner (Figure 2).

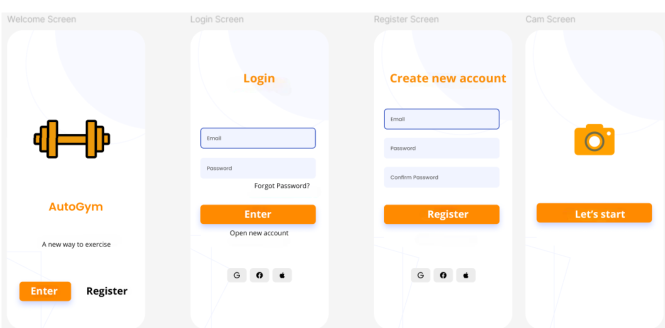

Fig. 2. Interface mockups of the AutoGym mobile application, illustrating the welcome, login, registration, and camera activation screens designed to support user-friendly onboarding and exercise initiation.

While this study focuses on the technical feasibility of real-time movement recognition using computer vision, sustained user engagement is a critical factor in the success of rehabilitation applications. Clinical studies consistently show that the long-term effectiveness of rehabilitation is heavily reliant on compliance and motivation [28]. To that end, future versions of the app may include gamification elements, personalized feedback, and progress tracking features to encourage users to stick to their routines.

Currently, the mobile application is still in the development phase and has not yet been fully completed. The integration of the movement recognition algorithm with the mobile interface is ongoing, along with performance optimization to ensure a smooth user experience. Some of the challenges faced so far include adapting the computer vision model to devices with different processing capabilities, ensuring low latency for real-time feedback, and designing an interface that balances functionality and simplicity.

V. Conclusions

This paper describes the design process for a smartphone-based rehabilitation system with focus on remote monitoring and real-time feedback for muscle rehabilitation exercises. The system leverages state-of-the-art pose estimation algorithms and machine learning models that can estimate movement accuracy and provide corrective feedback without relying on expensive or specialized hardware. The pipeline demonstrates the importance of data collection, pose estimation, feature extraction, and anomaly detection to ensure exercises are performed efficiently and safely.

By using unsupervised anomaly detection algorithms, e.g., Autoencoders and Isolation Forest, the system can adapt to different users and exercises, offering personalized feedback even without large labeled datasets. This approach has the potential to overcome the barriers of traditional rehabilitation methods, offering an accessible solution for patients who may face challenges in attending in-person therapy sessions.

While construction of the complete system is ongoing, the suggested pipeline provides a stable base for developing an efficient, user-friendly, and scalable rehab tool. Further steps involve developing the dataset, the machine learning models, integrating them into a mobile application, and constructing a seamless, intuitive user interface for multiple platforms.

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