ADAPTIVE PERSONALIZED EXERCISE PLAN AND REAL-TIME MOTION DETECTION

Final Project Thesis

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The dissertation was submitted in partial fulfilment of the requirements for the B.Sc. (Honors) degree in Information Technology

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DECLARATION

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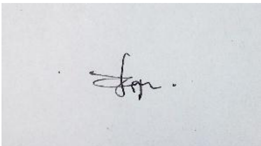
Signature:  Date: 4/11/2025

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ABSTRACT

The increased demand for assistive devices with personalized rehabilitation features for hearing impaired and lower-limb disabled individuals has led to the integration of artificial intelligence and real-time monitoring systems into assistive devices. The emphasis of this research is the implementation and creation of an Adaptive Personalized Exercise Plan and Real-Time Motion Detection as a key feature of a smart wheelchair solution. The system is meant to recommend personalized upper-body exercises specified for the neck based on user-specific input such as age, gender, injury type, and fitness level.

Initially, user data is collected via a web application and stored in Firebase. A Raspberry Pi processes this data and runs a cosine similarity-based machine learning algorithm to generate five customized exercises based on a pre-existing database. Users can initiate their workout via the web interface or through voice commands. The system uses a Raspberry Pi camera and the MediaPipe library for pose estimation in real-time, body landmark tracking to track the movement precision, symmetry, and number of repetitions. Real-time feedback is provided to modify injurious postures, and full performance data are uploaded to Firebase continuously.

A progress report is generated and assessed every month, which leads to a second model suggesting adaptation and optimization of the exercise routine based on trends in performance. Technologies used are MediaPipe for pose tracking, OpenCV for video processing, Scikit-learn for similarity calculations, and FastAPI for API integration. Results show how the system excels in being able to supply personalized, correct, and adaptable rehabilitation assistance in an efficient way, greatly enhancing user experience and safety. The component helps plug the gap existing assistive technologies by offering wise, user-aware rehabilitation capabilities addressed to individual conditions.

Keywords: Adaptive Exercise Plan, Real-Time Feedback, Pose Estimation, Rehabilitation, Personalized Recommendation.

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LIST OF ABBREVIATIONS

Abbreviation	Definition
AI	Artificial Intelligence
IoT	Internet of Things
WHO	World Health Organization
FDA	Food and Drug Administration
HTML	Hypertext Markup Language
CSS	Cascading Style Sheets
ML	Machine Learning
IT	Information Technology
UI	User Interface

1. INTRODUCTION

With developments in healthcare in the past few years, the merger of medicine and technology has introduced doors for high-tech assistive technologies for conquering challenges in individuals with disabilities. The intelligent wheelchair, one of them, is a promising innovation that entails enhanced mobility, security, and autonomy. However, alongside the development made in technology, current intelligent wheelchair systems have been primarily directed at navigation and barrier avoidance while omitting the valuable aspect of physical rehabilitation, particularly among hearing disabled and lower body disabled users. Such users commonly depend on caregivers or therapists to guide them in exercise routines that are occasionally unavailable due to insufficient accessibility, constrained healthcare delivery, or communication limitations.

Rehabilitation exercises, especially those for the upper limbs such as neck movements, are essential in maintaining mobility, preventing muscle stiffness, and general physical well-being. Rehabilitative methods, however, are less flexible, not real-time monitored, and not customized, which are essential in ensuring the safety and effectiveness of exercise programs. Besides this, deaf patients are also likely to struggle receiving corrective feedback during physical therapy classes and are therefore at more risk of poor posture or inconsistent exercise routines. These limitations produce a significant gap in current solutions for rehabilitation and necessitate an intelligent, responsive solution.

This research suggests a new solution: An Adaptive Personalized Exercise Plan and Real-Time Motion Detection System on a smart wheelchair platform. This system leverages the use of machine learning, computer vision, and IoT to enable the fully responsive and automated rehabilitation experience. The solution is two-pronged: first, the system creates an individualized list of exercises per user based on demographic and clinical factors like age, gender, type of injury, and physical fitness level by applying a cosine similarity-based recommendation model. Second, while the user performs exercises, a Raspberry Pi-linked camera constantly tracks the user's movement with MediaPipe and OpenCV and gives immediate feedback on posture, form, symmetry, and reps.

Real-time performance data is stored in Firebase, and hazardous or erroneous movements trigger instant alerts through the web interface to promote user safety. Every month, an automatically produced progress report is examined and evaluated. Through analysis, a second machine learning model updates the exercise suggestions to the user's evolving physical needs. The system operates all machine learning models locally on the Raspberry Pi with low latency and offline availability, which is highly critical to users in rural or underserved locations.

This component not only enhances the health outcomes of people with mobility and hearing disabilities but also encourages independence, participation, and consistency in their rehabilitation process. It addresses an essential gap in assistive technology by combining intelligence, customization, and interactivity into one platform. The following parts of this chapter review the literature that is found on this topic, suggest the research gap, define the key research issue, and present the objectives that guided the development and implementation of this system.

1.1 Background Literature

The development of assistive technologies, particularly in the fields of artificial intelligence (AI), Internet of Things (IoT), and computer vision, has led to more intelligent and personalized healthcare solutions for physically disabled individuals. Among these technologies, smart wheelchairs have been a central point of focus, offering not only enhanced mobility but also the potential to incorporate advanced features such as health monitoring, pathfinding, voice/gesture control, and interaction with the environment. However, despite their spread, most current smart wheelchair systems are restricted in scope on the physical side of navigation and obstacle detection, neglecting a core sector of user health: rehabilitation and physical therapy [1].

Rehabilitation is a critical part of regular care for lower body disabled individuals. Particularly, upper body exercises, including movements of the neck and postural re-alignment, are required to maintain muscular balance, prevent stiffness, and avert secondary complications such as pressure ulcers or spinal mal alignment. These complications worsen in users who spend long hours working while seated without programmed physical exercise. Besides, hearing-impaired people face obstacles in receiving conventional rehabilitation treatments, e.g., difficulty in receiving auditory instructions, interpreting feedback, or engaging in supervised exercise sessions. This points to a highly significant need for automated, real-time, and tailored rehabilitation support embedded in assistive mobility systems [2].

Some earlier studies have attempted to implement AI-based fitness training systems or remote physiotherapy services using wearable sensors, mobile apps, and motion detection platforms. These systems tend to use general activity recognition algorithms and are designed for large numbers of people. However, they usually do not account for individuals with specific disabilities or tailor the therapy to personal characteristics like age, type of injury, and starting level of fitness [3]. On the other hand, recommendation systems based on personalization, especially those applying cosine similarity algorithms, have proven to be very successful in suggesting relevant actions or content based on user similarity profiles. In the medical field, the same algorithms have been used to recommend diet regimen, medication, and even training regimens in sports programs. By calculating vector similarity between the user's input profile and a pre-defined rehabilitation exercise database, an extremely pertinent and personalized exercise list can be selected [4].

Moreover, real-time monitoring of exercises has been made more accessible with pose estimation libraries such as MediaPipe, which calculate human body landmarks (e.g., nose, shoulders, elbows, chin) from a standard RGB camera without the need for special hardware. This obviates the requirement of wearable sensors and enhances affordability and usability. MediaPipe's pose detection accuracy combined with lean deployment on edge devices like Raspberry Pi makes it an appropriate choice for embedded systems for smart assistive devices [5].

Along with pose detection, OpenCV—a strong open-source computer vision library—offers video capture and processing capability to monitor movements continuously. Through the combination of OpenCV and MediaPipe, systems can detect erroneous repetitions, assess symmetry and movement height, and flag potentially hazardous postures in real-time. For example, if a user is not maintaining symmetry during a neck flexion exercise or fails to achieve the anticipated movement angle, the system can instantly alert the user and record the event [6].

Data storage and transfer among the embedded hardware and user interface is managed by Firebase, which also acts as the real-time cloud database. User profiles, exercise histories, and progress reports are saved in it, making them accessible to users and caregivers in a centralized manner. In addition, the system employs FastAPI, a new web framework developed on top of Python, for API construction that allows for secure communication between front-end web-based interfaces and back-end ML services. For exercise classification and adaptation, threshold models are also employed. These models offer ranges of motion that are safe (e.g., 45°–90° neck rotation), and corrective feedback is provided if the user's movement does not exceed these thresholds [7].

Despite the existence of these individual technologies, very little work or products have sought an integrated, holistic approach that unifies recommendation systems, motion tracking in real time, adaptive feedback, and embedded processing in the guise of a single smart wheelchair platform—precisely one for dual-challenged individuals (i.e., both lower-body challenged, and hearing challenged). This project bridges this gap by suggesting a personalized rehabilitation aspect that offers robotic, smart exercise support to individuals, which makes them healthier as well as independent.

1.2 Research Gap

While advancements in intelligent assistive technologies have greatly improved mobility and independence for physically disabled individuals, there is a pressing need for the integration of intelligent rehabilitation features, especially for users requiring continuous upper-body rehabilitation and who have communication problems due to hearing disabilities. The current generation of smart wheelchairs primarily focuses on mechanical features such as obstacle detection, path planning, joystick substitution, and prevention of falls [1], [8]. Such systems efficiently support locomotion but ignore equally important aspects of long-term health and musculoskeletal maintenance, particularly for wheelchair-bound patients who are seated for prolonged hours.

It may result in severe secondary complications like muscle atrophy, postural disturbances, cervical spine deformity, and chronic pain if there are no directed exercises of the upper body when using a wheelchair—complications that are widely documented in clinical rehabilitation literature [9], [10]. Even though physical therapy has some alternatives, it is not always accessible to all users, especially in rural or resource-lack communities. Furthermore, hearing-impaired individuals are faced with restrictions in getting traditional therapy that is based mostly on verbal commands, auditory feedback, or on-site monitoring, making them most vulnerable to incorrect movements during self-rehabilitation [2], [11].

Existing AI-driven fitness or physiotherapy systems are mainly designed for general population fitness tracking, which is not precise enough and not individualized enough for safe rehabilitation in disabled groups. For instance, smartphone apps using wearable sensors (e.g., accelerometers or gyroscopes) or vision-based motion tracking usually provide pre-set exercise protocols without dynamically tailoring them to the user's unique characteristics—like their age, injury type, physical abilities, or previous progress [3], [12]. They aren't time-warped and feedback loops that alter with the modification of the user. Moreover, even though recent technologies such as MediaPipe and OpenCV are showing very accurate results in video processing and pose estimation in real-time, it has primarily remained limited to domains other than clinic such as gestures to control UIs, fitness apps, yoga tutorials [13], [5]. These deployments are usually run on high-end servers or require constant internet connectivity, making them inappropriate for offline, embedded rehabilitation systems in low-resource settings or on handheld devices. The possibility of running pose estimation models locally on edge devices such as Raspberry Pi based on light algorithms without the need for a cloud server has not been fully explored in the personalized rehabilitation domain [14].

Another important limitation is the lack of integration across the rehabilitation workflow. Most existing solutions that attempt real-time exercise tracking fail to integrate performance metrics with recommendation systems. They fail to use historical performance data (e.g., repetition accuracy, movement symmetry, hazardous posture frequency) to dynamically change future exercise recommendations. Thus, users are offered static plans regardless of their progress or regression. The need for an adaptive system based on reports of monthly evaluation to automatically adjust exercise regimens through machine learning is apparent and pressing, especially in rehabilitation facilities with a long-term nature [4], [15].

Moreover, while some researchers have explored rule-based or threshold-based posture correction algorithms, these systems typically consider only a small subset of movements and lack elaborate evaluation schemes that involve symmetry analysis, rep counts, and movement angle tracking [7], [16]. Even if such analysis exists, it is rarely supplemented with an intuitive interface providing real-time feedback in the form of visual cues, speech synthesis, or on-screen instructions—facilities crucial for hearing-impaired users.

Lastly, from a systems integration point of view, there is very little research that brings together all the following elements into a coherent, real-time rehabilitation system:

- User-specific exercise suggestion using cosine similarity and historical datasets,
- Real-time monitoring through camera-based pose estimation (e.g., MediaPipe),
- Threshold-based classification to identify dangerous or inefficient postures,
- Performance monitoring saved in a real-time database (e.g., Firebase),
- Progress-based dynamic exercise plan adjustment through machine learning models
- Edge-device deployment to support offline computation, e.g., via Raspberry Pi,
- Multimodal support interface options (e.g., web app and voice commands),
- And data-free communication via FastAPI and Firebase integration.

This feature set is nonexistent so far in academic, too, as well as commercial, solutions, especially designed for hearing-impaired wheelchair user individuals. Reducing the research gap addressed here has promise to revolutionize assistive healthcare technologies' accessibility, safety, and customization at the rehabilitation phase.

System/Reference	Upper Body Exercise Focus	Real-Time Motion Detection	Adaptive Feedback Mechanisms	Neck Exercise Specialization	Personalized Exercise Plans
Wilroy et al. [1]	✅ Yes	❌ No	❌ No	❌ No	✅ Yes
Sol et al. [2]	✅ Yes	❌ No	❌ No	❌ No	✅ Yes
Hwang and Jeon [3]	❌ No	❌ No	❌ No	❌ No	❌ No
Beomsoo and Doyoung [4]	❌ No	❌ No	❌ No	❌ No	❌ No
Lee et al. [5]	❌ No	❌ No	❌ No	❌ No	❌ No
PROPOSED SYSTEM	✅ Yes	✅ Yes	✅ Yes	✅ Yes	✅ Yes

Table 01 – Identifying Research Gap 1

1.3 Research Problem

Individuals with hearing disability and lower-body impairment face incredible challenges in daily living, particularly rehabilitation and mobility. While assistive technologies have come a long way, solutions today do not address the needs of individuals with both hearing disabilities and physical impairment, particularly exercise and rehabilitation. Specifically, individuals with mobility impairments, such as wheelchair users, struggle to have an active and healthy lifestyle because there are no integrated, individualized rehabilitation systems in conjunction with their mobility aids.

Current smart wheelchair technologies are primarily focused on increasing mobility through self-piloting, collision detection, and user control by using switches or joysticks. However, these kinds of systems hardly incorporate rehabilitation components, such as adaptive exercise and feedback, which are needed in maintaining total health and preventing conditions like muscle atrophy and postural impairments, particularly on users with long-term sedentary habits. Studies have shown that prolonged sitting, which is a common issue in individuals with mobility disabilities, can lead to several health complications, including muscle weakness and postural deformities (Craven et al., 2020) [9]. Besides, poor rehabilitation exercises, especially for the upper limbs and neck, also contribute to these issues, leading to a decrease in the quality of life among users.

For users of wheelchairs, exercises for the neck are necessary for ensuring correct posture and avoiding degeneration of muscles (Feldman, 2019) [10]. Though they are crucial, present rehabilitation systems for people with mobility disabilities do not usually provide special exercises for the neck or upper body. Present systems are mostly generic, not adjusting to the progress of the individual and the needs of rehabilitation. Rehabilitation technologies that provide real-time feedback according to individual performance and adjust plans are clearly lacking (Mathur & Thomas, 2022) [12]. This lack of personalized rehabilitation is further exacerbated for deaf individuals since they are also hampered by challenges in communicating with their devices.

Additionally, posture and movement monitoring for the purposes of rehabilitation exercises tend to be of a limited scope. Most current systems employ simple visual feedback to adjust posture (Lugaresi et al., 2019) [13], but these systems are not elaborate enough for effective rehabilitation, particularly for exercise involving dynamic movement, such as neck exercises. Sophisticated computer vision techniques, such as real-time pose estimation through MediaPipe (Lugaresi et al., 2019) [13] and other similar frameworks, have shown promise for motion tracking but are currently not integrated in rehabilitation devices for mobility-impaired individuals. Such a system would be capable of delivering meaningful real-time feedback about movement and posture during exercises, helping users maintain good form and progress through their rehabilitation programs.

Therefore, the research problem is to design an entire smart wheelchair system that enables personalized and adaptive rehabilitation for the hearing-impaired and lower-body disabled population. The system should include:

1. **Adaptive rehabilitation exercises**: The system must provide real-time feedback for rehabilitation exercises, particularly for the upper limbs and neck, and adjust the exercises based on the performance and improvement of the individual. This would bridge the current gap of adaptive rehabilitation systems for wheelchair users (Craven et al., 2020) [9].

2. **Real-time pose tracking and feedback**: The system should utilize advanced computer vision techniques like MediaPipe to track the user's posture and provide real-time feedback on exercise performance. This would be specifically important for neck exercises, whose performance requires precise movement (Lugaresi et al., 2019) [13].

3. **Comprehensive health surveillance and rehabilitation inclusion**: The machine must incorporate mobility support along with the rehabilitation function in one device that provides mobility support and real-time feedback during rehabilitation to the users. Dual functionality would assist in avoiding the requirement for the use of multiple machines to meet diverse needs, which in turn enhances the overall welfare and quality of life (Mathur & Thomas, 2022) [12].

This study aims to solve these issues by developing a smart wheelchair system that integrates mobility, rehabilitation, and communication features seamlessly. It aims to supplement existing systems with a more integrated approach that addresses the specific needs of patients with hearing disabilities and lower-body disabilities. Through targeting adaptive rehabilitation exercises, real-time motion detection, and gesture control, the proposed system could significantly enhance the autonomy and rehabilitation experience of these users.

1.4 Research Objectives

The primary aim of this research is to develop an intelligent wheelchair system with customized rehabilitation, gesture-based control for hearing-impaired users, and real-time motion tracking for improved mobility and rehabilitation in hearing-impaired and lower-body disabled individuals. The system will provide customized rehabilitation plans, posture and movement tracking, and real-time feedback to provide correct exercise performance by the users, and promote autonomy, comfort, and well-being.

1.4.1 General Objective

To develop and release an intelligent wheelchair system with mobility assistance along with personalized rehabilitation exercise, gesture-controlled hearing-impaired patients, and real-time motion tracking for improved rehabilitation outcomes, improve the quality of life, and enable more independence of hearing-impaired and lower-body impaired patients.

1.4.2 Specific Objectives

To develop an adaptive rehabilitation system that can dynamically adjust exercise schedules based on the progress and performance of the user and give the best possible rehabilitation for individuals who have disabilities in the lower body. The system will handle primarily neck and upper-body exercises, with emphasis on providing immediate feedback on posture and movement (Feldman, 2019) [10]. With the employment of adaptive algorithms, the system will benefit the wide variety of individuals who lack mobility, improving the general rehabilitation process.

1. Incorporating real-time pose estimation and motion analysis using computer vision technologies, e.g., MediaPipe, to track and monitor the user's posture during the period of rehabilitation training. The system will ascertain precision

of movement, identifying any distortion from the prescribed posture, and provide corrective feedback in real-time (Lugaresi et al., 2019) [13]. This should assist users to exercise accurately to avoid further harm or discomfort as well as assure maximum rehabilitation efficacy.

2. To design an adaptive rehabilitation exercise recommendation system that can adjust rehabilitation plans based on real-time performance. The system will analyze user performance through comparison of prescribed movement with actual movement, and suggest exercise intensity, repetitions, and sets. This personalized approach will ensure that users are constantly doing exercises that are appropriate to their existing capability and rehabilitation progress (Mathur & Thomas, 2022) [12]. The system will also give users monthly progress reports and adjust the exercise program according to data collected, ensuring continuous improvement.

3. To create an accessible and user-friendly user interface (UI) for the wheelchair system usable by mobility-impaired and hearing-impaired individuals. The UI will facilitate ease of use by users with minimal settings adjustments for the rehabilitation exercises, wheelchair control, and health checking, via combined touch, gesture, and voice inputs. A hearing-impaired-friendly user-friendly interface will be designed with visual aid integration and gesture recognition, offering high accessibility and user-friendliness.

4. To validate the usability and effectiveness of the smart wheelchair system through user trials and feedback collection. Testing will establish how well the system can enhance rehabilitation outcomes, enable greater mobility, and enhance autonomy. User satisfaction will be tracked through survey and interview mechanisms, while clinical outcome will be tracked using performance metrics like accuracy enhancement in exercising, mobility, and health monitoring data. Such feedback through these mechanisms will facilitate optimization of the system to align it with the target user group requirements.

5. To establish the viability and scalability of the system through evaluation of the combination of hardware and software, ensuring that the solution is economical, efficient, and feasible for mass use. This will involve examining the parts of the system to establish their longevity, user-friendliness, and integration with existing wheelchair models. The research will also consider the scalability of the system, examining how it can be adapted for a massive number of users with different types and levels of mobility impairments.

6. To develop an integrated system of training and assistance for users and caregivers that involves tutorial guides on wheelchair operation, exercise tracking, and gesture control system. The assistance system will also constantly support and update users according to their progress, offering them necessary resources to optimize their rehabilitation process. Such support will be crucial to enable the easy integration of the system into the daily lives of individuals with mobility and hearing impairments.

By achieving these specific objectives, this research aims to fill gaps in the application of assistive technologies that develop an overall solution not only addressing the mobility challenges that accompany lower-body disabilities but also empowering individuals with hearing disabilities to participate and use the system through gesture commands. The resulting system will promote rehabilitation, independence, and general health, maximizing the quality of life of users while pushing the boundaries of current assistive technology.

2 METHODOLOGY

The methodology chapter of the present study presents the sequential methodology adopted to conceptualize, design, and experiment with the proposed smart wheelchair system. The methodology is designed to address the research problem through a hardware-software-based integration of different technologies such as real-time motion tracking, gesture-based control, adaptive rehabilitation, and personalized exercise recommendations. This technique integrates cutting-edge computer vision, machine learning, and real-time health monitoring to offer an innovative solution with enhanced mobility and rehabilitation experiences for deaf and lower body disabled users.

The research adopts a multi-stage strategy, starting with conceptual design and system architecture, proceeding to development of the individual components of the system, and ending with testing, evaluation, and ultimate implementation. Each stage is informed by the specific research objectives and is focused on ensuring that the final product is effective as well as feasible in actual usage. The methodology also considers commercial feasibility and acceptability by the users, and the objective of making the product accessible, reliable, and scalable.

Here, in this section, the precise research and development process steps and the commercialization plan, testing plan, and implementation plan will be explained. Technical aspects as well as practical considerations along with an emphasis on user-centric design so the system serves the targeted population appropriately have been considered while keeping the approach in mind.

2.1 Methodology

The Adaptive Personalized Exercise Plan and Real-Time Motion Detection system integrates machine learning, computer vision, and real-time monitoring to provide a personalized rehabilitation system for the disabled hearing and lower-body impaired individuals. The system process involves several stages, from the collection of user data and generation of personalized exercise plans to continuous monitoring and exercise adjustment based on performance feedback. This method is aimed at ensuring that users are doing exercises pertinent to their specific needs and abilities and allow for real-time correction to ensure safety and effectiveness. The sequential steps of the method are then outlined.

Step 1: User Profile Gathering and Exercise Plan Creation

The first phase of the system is to obtain the user's information through a web application. The user is asked to fill out a form with relevant information, including age, gender, nature of injury, fitness level, and other relevant health information. This is crucial as it forms the basis of the tailored exercise suggestions that the system will generate.

The information gathered is uploaded to a Firebase database, where user information and exercise performance information are centrally stored. The Raspberry Pi downloads the information and acts as the local processing unit of the system. It logs into Firebase and downloads the necessary user information to run the first machine learning model, which generates the first set of five suggested exercises.

The process of suggesting exercises is motivated by the cosine similarity algorithm, which computes similarity between the user profile and a stored set of exercise profiles in a database. Exercise is represented by a feature vector through parameters such as intensity, movement needed, and difficulty. Cosine similarity is used to match the profile of the user with the most suitable exercises from the dataset to have the exercises tailor-made to satisfy the user's specific requirements considering their fitness level, injury, and mobility limitation.

This initial recommendation model chooses five exercises that are both convenient and helpful for the rehabilitation of the user. The user is then invited by the web app to begin the exercises either by clicking a "Start" button or by giving voice commands, making it accessible to people with varying abilities, particularly those with limited mobility or the deaf.

Step 2: Real-Time Monitoring and Performance Evaluation

Once the exercises have been initiated by the user, the system utilizes a camera that is attached to the Raspberry Pi to record real-time video of the user's movements. The camera is instrumental in tracking the accuracy of the user's performance of every exercise to ensure that they move according to the right motion paths and that they execute the exercises safely.

MediaPipe, an open computer vision framework with real-time pose estimation capability, is employed to analyze the video stream coming from the camera. MediaPipe tracks major body landmarks, such as the shoulders, elbows, and neck, along the duration of the exercise so that the system can monitor the movements with good accuracy. The system checks whether the user's posture and movements meet the perfect execution of the individual exercise.

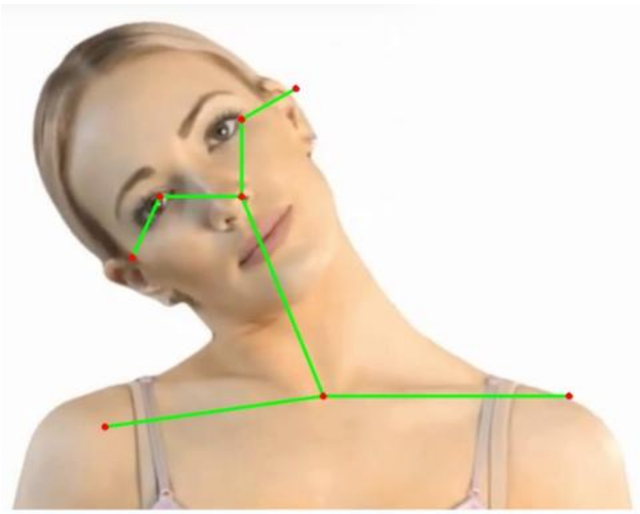

Figure 01 - Body Landmarks 1

For each exercise, the system employs threshold-based classification to detect and classify specific movements such as neck extensions, chin tucks, and other targeted motions. Threshold-based classification ensures that correct movements are the only ones registered as repetitions and that users cannot do the exercise incorrectly or in a way that can be harmful. For instance, the system would only log the repetition if the user's neck were capable of being raised at least to a 90-degree angle for the neck extension exercise. This feature is particularly important to the safety of the user as well as to the logging of significant performance.

The system also checks for symmetry in movements of the user. The symmetry analysis guarantees that the user is exercising both sides of their body equally, a critical aspect in rehabilitation, especially for individuals with mobility impairments. If asymmetry is detected, the system can recommend compensation in the exercise to correct the imbalance and provide improved performance.

Along with symmetry, the system also tracks movement height and repetitions, providing additional indicators to gauge exercise quality. The user's performance is graded on these parameters, and feedback is immediate through the web app. Feedback in the form of recommendations to improve posture, increase movement height, or accomplish higher repetitions is provided, depending on the result of the performance test.

Step 3: Real-Time Feedback and Adjustment

As the user progresses through exercises, the system provides the user with real-time feedback through the web application. This feedback plays an important role in guiding the user as well as ensuring the user exercises in a safe and efficient manner. The feedback is visual and audible. If the posture of the user is incorrect or can be hazardous, such as performing a neck extension with very little range or in an improper alignment, the system will notify the user through the web application, providing instructions on how to restore the correct posture.

The feedback system relies mostly on the performance assessment parameters—symmetry, movement height, repetitions, and posture correctness—so that every aspect of the exercise is addressed. In addition, OpenCV is used to treat the video in real-time such that posture errors can be identified and the feedback offered at once. OpenCV's image processing allows the system to monitor and analyze the user's movements precisely even in challenging conditions such as low light conditions or small variations in exercise technique.

This real-time monitoring and feedback loop is an essential part of the system, as it not only ensures that users are performing exercises correctly but also immediately alerts them to any errors that could hinder their progress or cause injury. The web application thus becomes a learning and motivational aid, giving users the chance to continuously improve their form and rehabilitation outcomes.

Step 4: Adaptive Exercise Adjustment and Progress Report Generation

The system creates a progress report after each exercise session. The report is detailed, presenting detailed records of the user's performance. These include summary measures such as repetitions number, movement quality, symmetry, and posture accuracy. The system automatically stores the progress report into the Firebase database, creating a comprehensive log of the user's exercise history.

Each month, the system examines the aggregate performance data gathered to evaluate the progress of the user and identify areas that need tweaking. Based on this analysis, the second model of recommendations is triggered, which adjusts the user's exercise plan for the following month. The second model utilizes the historical performance data to suggest changes such as increasing the level of exercises, adding more challenging movements, or simplifying exercises for users with poor performance.

The second type of recommendation model adjusts the exercise routine dynamically by processing data. If a user demonstrates consistent improvement in their exercise routines, the system would be able to increase the level of exercises, e.g., add extra repetitions or even introduce new exercises to challenge the user further. Alternatively, if the user is struggling with some of the movements or is not making a lot of progress, the system can suggest changing the exercises to make them simpler, helping to keep the user engaged without becoming frustrated.

The use of cosine similarity and threshold-based classification here ensures that the exercise suggestions are made according to both the individual performance history and physical capabilities of the user, offering an adaptive and dynamically varying rehabilitation regimen.

Step 5: Machine Learning Processing on Raspberry Pi

The entire machine learning process, both recommendation models and performance evaluation, is done locally on the Raspberry Pi. This design selection allows the system to compute video data and perform calculations in real time, without relying on remote servers for computation. The local calculation minimizes latency and gives feedback instantly to the user, enhancing the overall user experience and allowing real-time monitoring effortlessly.

The Scikit-learn library performs machine learning operations such as data pre-processing, similarity calculation, and invocation of the recommendation models. By running the models on the Raspberry Pi, the system reduces reliance on external servers for faster and more efficient use. Local processing is particularly important to users in locations with low internet connectivity, hence the system remains operational even in the case of interrupted cloud connectivity.

By localizing the entire process, the system also enhances privacy and security because all user data and exercise performance information are locally stored and processed within the user's environment, reducing risks associated with cloud data storage.

Below is a diagram of the flow of the process in simple 10 steps.

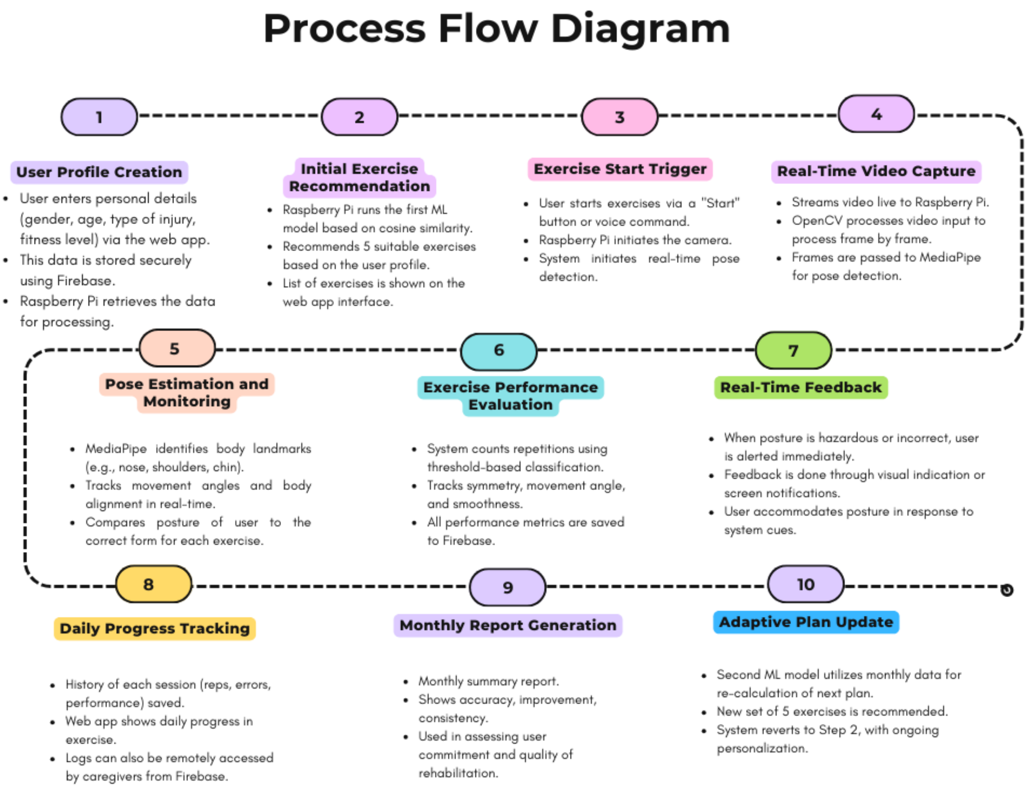

Figure 02 – Process Flow Diagram 2

2.2 Commercialization aspects of the product

Commercialization of Adaptive Personalized Exercise Plan and Real-Time Motion Detection system for people with hearing disability and lower body disability is contingent on several issues like product development, market opportunity, target market, revenue model, and scalability. Considering all such factors, the system holds significant potential to achieve great value within the assistive technology and rehabilitation markets and thereby offers an economical and effective alternative for users and healthcare providers.

Market Potential

The market for assistive technology is expanding rapidly owing to an increase in the elderly population, improved awareness of issues related to disabilities, and growth in technology. According to a World Health Organization (WHO) report, it is estimated that over 1 billion people around the world are living with some disability, and many individuals require assistive devices to improve their health. This provides great market potential for products created to aid mobility disabilities, as well as hearing disabilities.

The rehabilitation technology market is also expanding as more and more people are seeking individualized, in-home physical therapy. Traditional rehabilitation is time-consuming, and clinical visits based, limiting patient access for individuals with mobility impairments or those living in remote areas. An individualized exercise system like the one proposed, with potential of continuous and immediate feedback and exercise programs to accommodate changing needs, can induce a paradigm shift in home rehabilitation for patients with physical disabilities, especially neck injury and mobility impairments.

Target Market

The target market of the product is individuals with lower-body and hearing disabilities requiring physical therapy and rehabilitation. Specifically, the product would be promoted to:

- **Physically disabled individuals** (for example, patients with spinal cord injury, stroke patients, amputees, and patients who are elderly and have mobility disabilities).
- **Hospitals and rehabilitation centers**: Such centers would include the system as part of their physical therapy, and patients would be monitored remotely and given customized rehabilitation.

- **Home users**: Patients who have experienced surgeries or injuries may use this system at home for regular exercise and rehabilitation, which is particularly beneficial for those who are unable to attend physical therapy sessions in person.

Further, healthcare professionals such as rehabilitation therapists, physiotherapists, and medical device companies will be key stakeholders who might invest in or embrace this technology. The system can help therapists in the sense of enabling them to remotely track patients, track progress, and adjust exercises accordingly.

Revenue Models

The product presents several potential revenue streams, allowing flexible commercialization strategies:

1. **Subscription Model**: The rehabilitation centers or end-users can be charged with a yearly or monthly subscription for access to the web app, real-time feedback, progress reports, and personalized exercise plans. The subscription can also include cloud storage of performance data and regular updates in exercise plans based on performance metrics.

2. **One-Time Purchase**: The system can be sold as a one-time purchase, along with the necessary hardware (Raspberry Pi, camera) and software (web app and local processing) for home users or healthcare workers. A lifetime license or software maintenance agreement can be offered to offer continuous support and updates.

3. **Collaboration with Healthcare Providers**: Collaborating with rehabilitation centers, hospitals, or insurance companies to provide the system as part of an integrated rehabilitation program is another model. Providers can integrate the system into standard treatment plans at a premium fee for customized rehabilitation experience.

4. **Data Analytics Services**: With the system capturing huge volumes of performance data, another revenue model could involve selling anonymized and aggregated data to researchers, rehab centers, or insurance companies looking for healthcare analytics. This would enhance rehabilitation outcomes and practices as well as provide a secondary source of revenue for the product.

Scalability and Growth Potential

The system is highly scalable and, as such, flexible to accommodate diverse markets and user needs. Having Raspberry Pi as a local processing unit, coupled with cloud storage (Firebase), the system is capable of scaling effortlessly for diverse users, from one-person family users to large-scale rehabilitation centers. The modularity of the system allows it to be extended and customized, where new exercises or functionalities are added whenever necessary.

The main enablers for scalability are:

- **Customization and Localization**: The system is highly customizable according to different languages, locations, and healthcare needs. Because the system is operating on machine learning models to generate exercise recommendations, additional data of other populations may be integrated so that the recommendation becomes more specific and variable as per different populations.

- **Cross-Platform Integration**: The product could be integrated into current healthcare management systems or mobile health apps. Collaborations with other companies or startups working in the digital health space could increase the reach of the product.

- **Other Disabilities Expansion**: While the system currently focuses on neck exercises for hearing-impaired users and lower-body disabilities, there is immense potential for expanding the product to incorporate rehabilitation exercises for other disabilities. These might include exercises for users with other physical disabilities such as shoulder injuries, backache, or post-surgery recovery.

Challenges and Considerations

While commercialization of the system is of significant potential, several hurdles must be addressed to enable effective market adoption:

- **Regulatory Approvals**: Depending on location, the system may need to comply with medical device directives (e.g., the FDA within the United States or the CE mark in Europe) before it can be marketed as a treatment device.

- **User Adoption**: It is the user adoption that makes the system successful, based on whether users embrace the technology and integrate it into their rehabilitation program. This could involve education and training, especially for the elderly or those with minimal understanding about technology.

- **Data Privacy and Security**: As the system is recording health information that is sensitive, it is mandatory that the information should be protected, and users' privacy should be ensured as per laws such as HIPAA in the United States or GDPR in Europe.

- **Continuous Support and Improvement**: To maintain long-term success, the system needs to be continuously updated to improve the machine learning models, user experience, and introduce new features. Software updates, customer support, and interaction with the community will be essential in keeping a healthy user base.

2.3 Testing and Implementation

The Testing and Implementation phase of the Adaptive Personalized Exercise Plan and Real-Time Motion Detection module includes ensuring the system meets its functional, performance, and usability requirements. The system uses adaptive exercise plans specific to every user of the smart wheelchair depending on machine learning models that offer exercise suggestions and monitor real-time performance. The tests are for validating the correctness of the personalized recommendations, motion detection efficiency, and the usability of the entire system for end-users with mobility and hearing impairments. The section is for explaining the testing methodologies, implementation process, and deployment in the real-world steps.

2.3.1 Tools and technologies

The creation and implementation of the Adaptive Personalized Exercise Plan and Real-Time Motion Detection system included the utilization of numerous software libraries, hardware devices, and cloud platforms. Every one of the technologies was selected to offer real-time processing, accurate pose detection, personalized suggestions, and effective communication between components. The technologies and tools utilized in the development and deployment of the system are as follows:

1. **Programming Languages and Frameworks**

- **Python**: Main programming language used for machine learning models, image processing, and Raspberry Pi scripts.

- **ReactJS / HTML / CSS**: Used for creating the front-end interface of the web application.

- **FastAPI**: High-level Python web framework used to create RESTful APIs for inter-component communication.

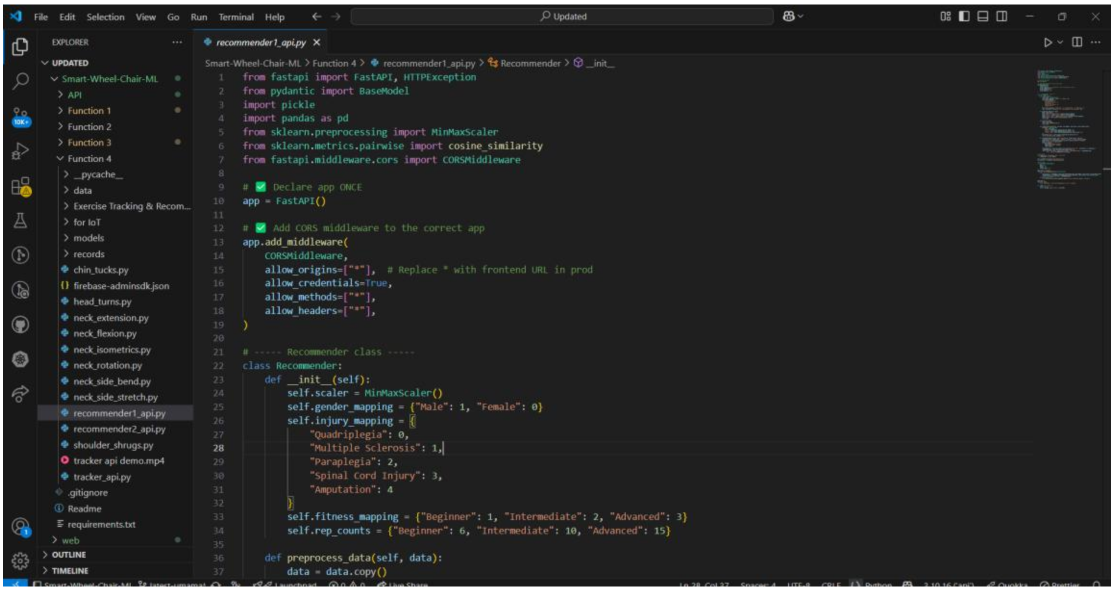

Figure 03 – Recommendation models 3

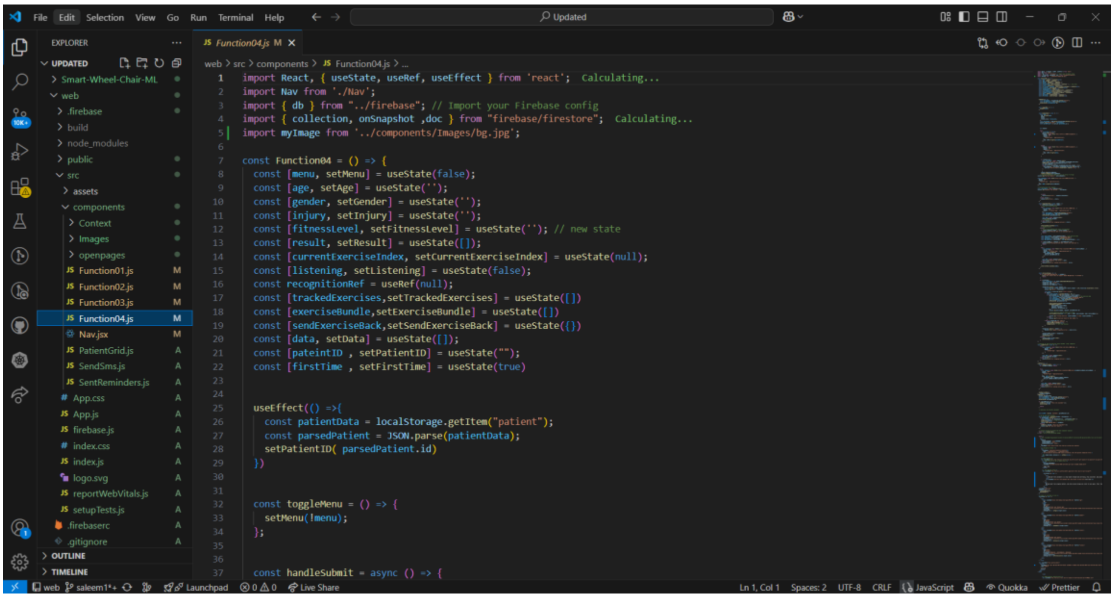

Figure 04 – Web app implementation 4

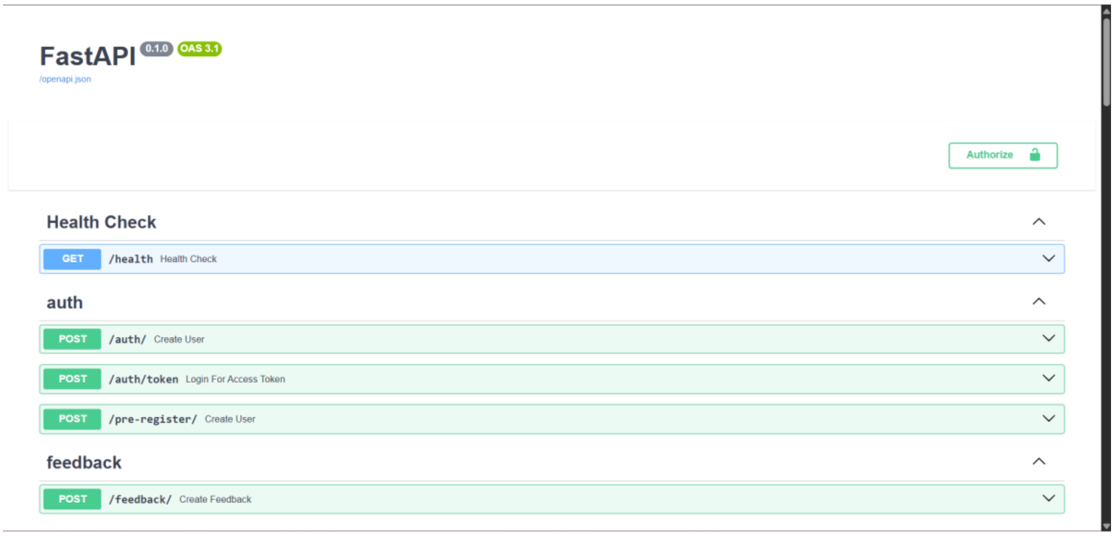

Figure 05 – Fast API endpoints 5

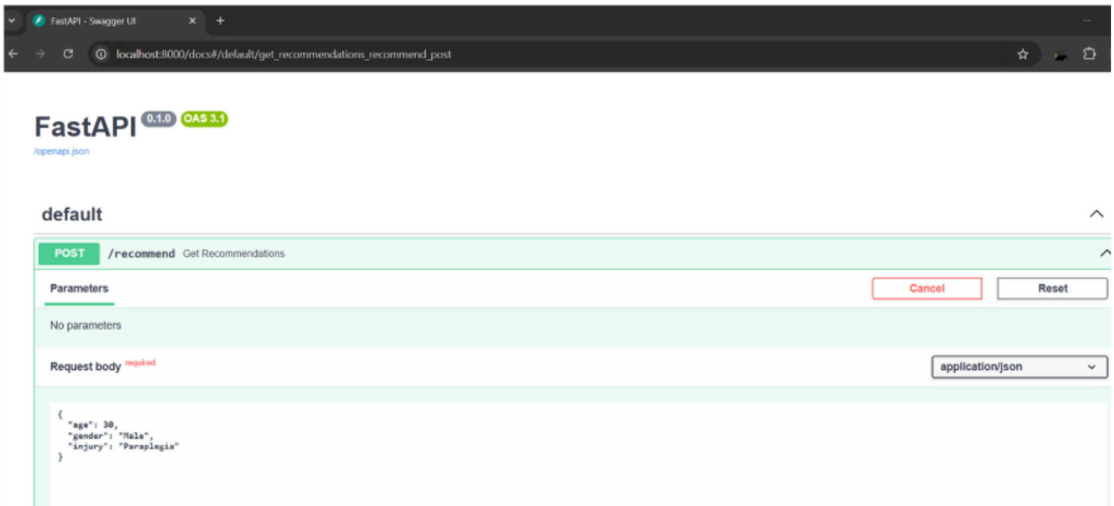

Figure 06 – Fast API execution 6

2. Machine Learning and Data Processing

- **Scikit-learn**: Used for implementing the cosine similarity algorithm and data preprocessing task.

- **NumPy / Pandas**: Employed for data manipulation, analysis, and vector operations within the ML models.

3. **Computer Vision and Pose Estimation**

- **MediaPipe**: Employed to detect and track human body landmarks, particularly neck and shoulder joints, for pose estimation.

- **OpenCV**: Handled video capture and real-time image processing from the camera feed connected to Raspberry Pi.

4. **Backend and Database**

- **Firebase**: A cloud-hosted real-time database that was used to host user profiles, exercise recommendations, and performance data. Also used for Raspberry Pi and web app syncing.

- **Firebase Authentication**: Enabled secure login and user authentication within the web interface.

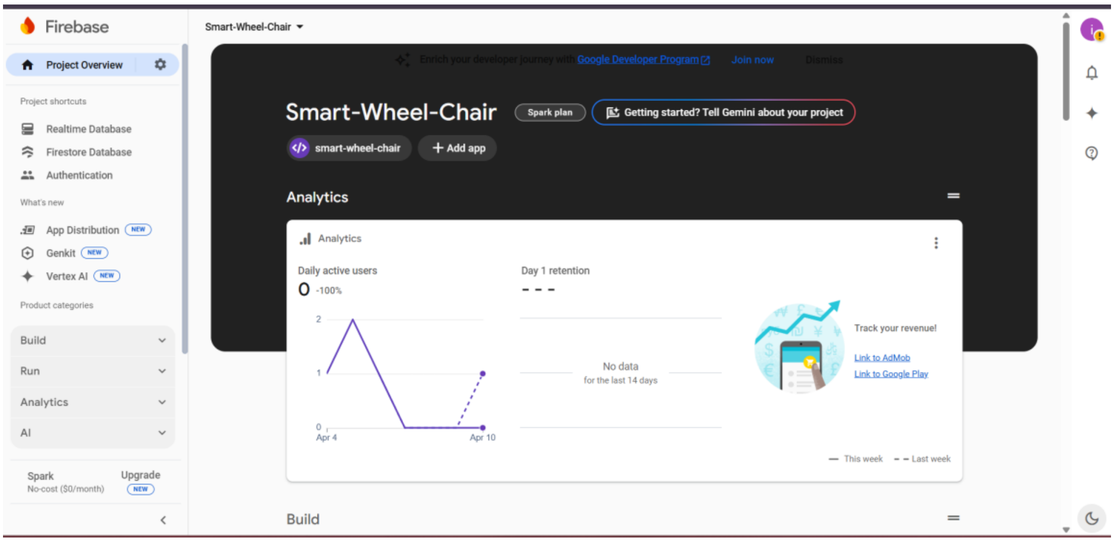

Figure 07 - Firebase 7

5. **Embedded Hardware and IoT**

- **Raspberry Pi 4 Model B**: The edge device that hosts the machine learning models, runs camera input, and conducts all local calculations.

- **Pi Camera Module**: Supplied captured real-time video feed for pose estimation and performance monitoring.

6. Web Technologies and UI

- **Voice Recognition API (Web Speech API)**: Added voice command functionality to start exercises, making it more accessible.

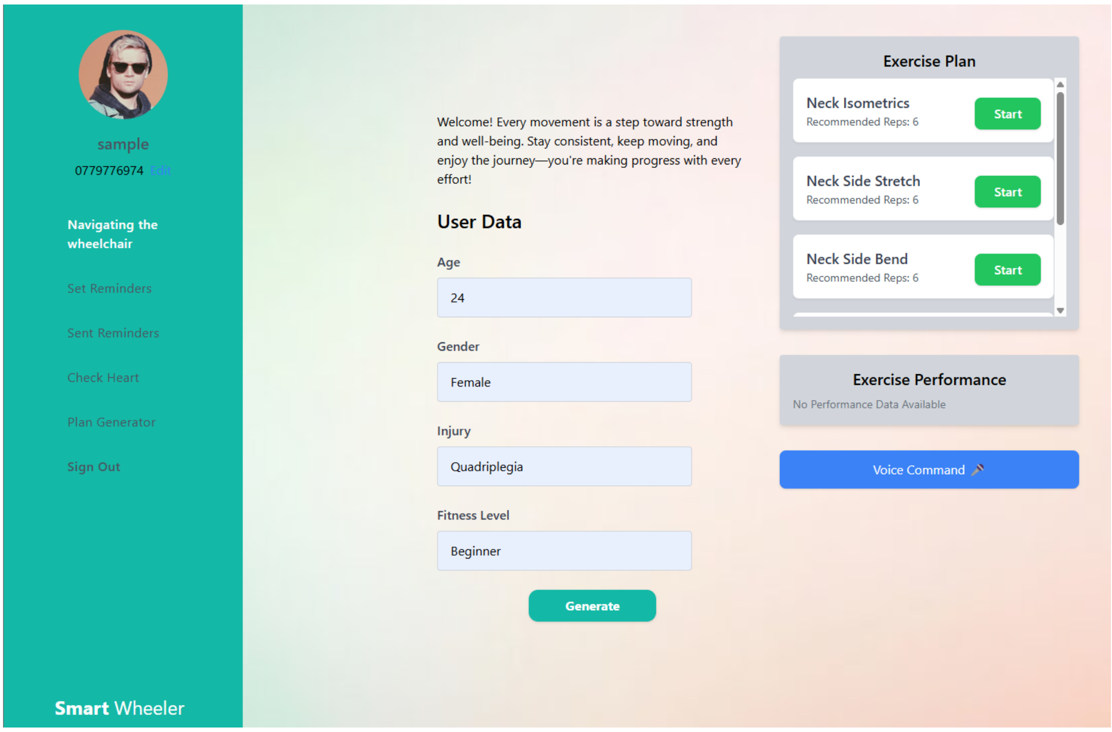

Figure 08 – Web UI 8

2.3.2 System Integration Testing

System integration testing assures that each part of the Adaptive Personalized Exercise Plan and Real-Time Motion Detection system harmonizes together properly. The major components tested include:

- **User Profile and Exercise Recommendation**: The process starts with acquiring user information such as age, gender, injury, and level of fitness from the web application. User data is computed on the Raspberry Pi depending on the FastAPI backend to invoke the first recommendation model. The system prepares five personalized exercises by computing Cosine Similarity, which relates to the user profile and suitable exercises. The integration test focuses on correctly passing user data into the recommendation model and suggesting five suitable exercises according to the model's output.

- **Pose Estimation and Motion Detection**: MediaPipe framework is utilized for motion detection and pose estimation. It tracks the body landmarks of the user (shoulders, neck, etc.) through the camera mounted on the Raspberry Pi. MediaPipe integration testing ensures that MediaPipe accurately follows the movement of the user during the exercise session and checks the angle and symmetry of the exercises (e.g., extension of the neck, chin tuck). This involves testing that the landmarks are correctly identified in real time across different users and scenarios such as varying lighting or camera locations.

- **Firebase Data Synchronization**: User data, such as performance metrics of repetitions, symmetry, and posture, are stored in Firebase. The feature of synchronizing the data with the backend and showing progress in real-time is tested. This is done so the performance of exercises is logged and can be retrieved for the sake of generating progress reports, which are fed back into the system's recommendation model for the next set of exercises.

- **Instant Notifications and Feedback**: The web application is designed to provide instant feedback about the performance of the user. The feature includes notifying the user when his/her posture is harmful or when he/she is about to deviate from the best form. System testing ensures that notifications and feedback are delivered at the appropriate moment so that the user can correct his/her posture in an instant. The testing ensures that feedback is timely and delivered in an intuitive way (e.g., visual cues on the web application or voice feedback).

2.3.3 Functional Testing

Functional testing ensures that the system's core functionality works as expected, especially in real-world usage scenarios:

- **Exercise Monitoring and Tracking**: Functional tests are performed to ensure that MediaPipe and OpenCV work together to monitor exercises properly. They include testing the tracking of body landmarks and movement detection such as neck extension or tucking chin. The threshold-based classification algorithm is tested to ensure that movements are correctly classified and measured. Testing is also put on the system's ability to track the repetitions number and symmetry of an exercise.

- **Personalization of Exercises**: Cosine Similarity model is a core component for personalized exercise recommendations. The Cosine Similarity model measures the similarity between the user profile and the exercises in the data set. Functional testing ensures the implementation of the Cosine Similarity algorithm and whether the recommended five exercises are appropriate for the user's fitness level, injury status, among other considerations. The system's ability to adjust the set of exercises after taking into consideration the user's progress is also tested.

- **Performance Evaluation**: The system carries out every exercise in comparison to key performance measures, e.g., symmetry, number of repetitions, and quality of movement. Functional tests are made so that performance measures are correctly calculated and monitored, and performance defects (e.g., low symmetry) trigger corrective hints. The aim is to inform the system regarding whether the user's movements require improvement and provide hints accordingly.

2.3.4 Usability Testing and User Testing

Since the system is focused on people with disabilities, particularly hearing and mobility impairments, user testing and usability testing are critical to ensure that the system is accessible and usable.

- **Usability Testing**: A group of users who are hearing impaired and have mobility issues will be selected to test the web interface of the system. The primary goal is to assess how easy it is for users to navigate the app, input personal data, and interact with the exercise recommendations. Feedback will be collected on the clarity of instructions, simplicity of use of the interface, and overall user satisfaction. This will ensure that wherever the system is confusing or difficult for users to collaborate with is identified.

- **Real-Time Feedback Evaluation**: Real-time feedback, including reminders on posture corrections and performance notifications, are critical to correct exercise performance. User testing will evaluate if and how feedback from the system is understandable and helpful. This will include checking whether visual and/or audio feedback is comprehensible, and whether users are motivated and supported by the system during their exercise sessions.

- **Adaptive Exercise Plan**: User testing will also evaluate the exercise plan's adaptability. After users complete a series of exercises, the system generates progress reports and adjusts the recommendations for the next month. Testing will ensure that the system adjusts the difficulty, or the type of exercises accordingly based on the user's progress so that the plan remains challenging yet achievable.

- **Voice Command Interaction**: Voice commands may be employed by certain users to start exercises or navigate through the app. The functionality will be tested to ensure that the voice recognition feature is reliable across different environments and easy to utilize, especially for users with minimal mobility.

2.3.5 Performance Evaluation

The performance assessment of the system ensures that it functions as expected in terms of speed, accuracy, and responsiveness:

- **Real-Time Performance**: The core capability of the system is based on real-time video processing and feedback. Testing involves observing latency of user motion and system response. How efficiently the system can handle live video and react with real-time feedback is crucial because delays could impact the user experience. Performance benchmarks will be determined to ensure that feedback is provided within a reasonable timeframe (e.g., within 1-2 seconds for each movement).

- **Pose Estimation Accuracy**: The precision of MediaPipe to identify and follow the user's body landmarks is validated in relation to movement type and diversity of user profiles. Accuracy tests will ascertain how well the system tracks key body points, particularly in the case of neck exercises, and how precisely it assesses quality of movement (e.g., degree of neck extension or flexion).

- **System Scalability**: Although the initial consideration is for a single user, the scalability of the system to accommodate multiple users in rehabilitation centers or clinics is also considered. The backend systems, which are Firebase and FastAPI, will undergo stress testing as far as holding multiple users at once without significant loss of performance. This means testing the database for handling and retrieving user data in real-time for multiple users at once.

2.3.6 Pilot Testing

Following functional, integration, and usability testing, pilot testing will subsequently be conducted in a live rehabilitation setting. When the pilot phases:

- **Deployment**: Deploy the system to a small set of users (e.g., the patients of one rehabilitation facility) for a significant period. Users will daily use the system, perform the exercises, and receive immediate feedback.

- **User Feedback**: User feedback will be collected using interviews and surveys to evaluate user experience, such as the usefulness of the personalized exercise suggestions, how easy it is to use the web application, and how useful the real-time feedback is. This information will drive any changes to the system's functionality and interface that need to be made.

- **Progress Monitoring**: The progress of the user will be monitored through the system's progress reporting capability. This allows for a determination of how well the adaptive exercise regimen works overtime, and whether adjustments to the exercise set are needed based on the user's evolving fitness level and performance.

2.3.7 Final Implementation and Rollout

Once it is successfully tested and pilot user comments are received, the system will be implemented at last and deployed on a full scale. This will comprise:

- **Commercial Deployment**: The system should be installed in healthcare professionals, rehabilitation centers, and personal users. Documentation, user guides, and customer support shall be provided to assist users in onboarding.

- **Regular Monitoring and Maintenance**: After the implementation of the system, it will be continuously monitored to ensure its performance and effectiveness. Regular updates and improvements will be conducted, based on user reviews and advances in machine learning and rehabilitation technologie

By rigorously testing all aspects of the system, from individualized recommendation to real-time feedback, the implementation process ensures that the Adaptive Personalized Exercise Plan and Real-Time Motion Detection system is reliable, effective, and accessible for users with mobility and hearing impairments.

2.3.8 Test Scenarios and Results

Scenario	**Expected Result**	**Outcome**
Start exercise with profile match	Exercise plan loads correctly	Passed
Pose detected within threshold	Repetition counted	Passed
Neck angle exceeds safe limit	Alert generated	Passed
Exercise session completed	Session logged in Firebase	Passed
Monthly report generated	Adjusted exercise plan shown	Passed

Table 02 – Test Scenarios and Results 2

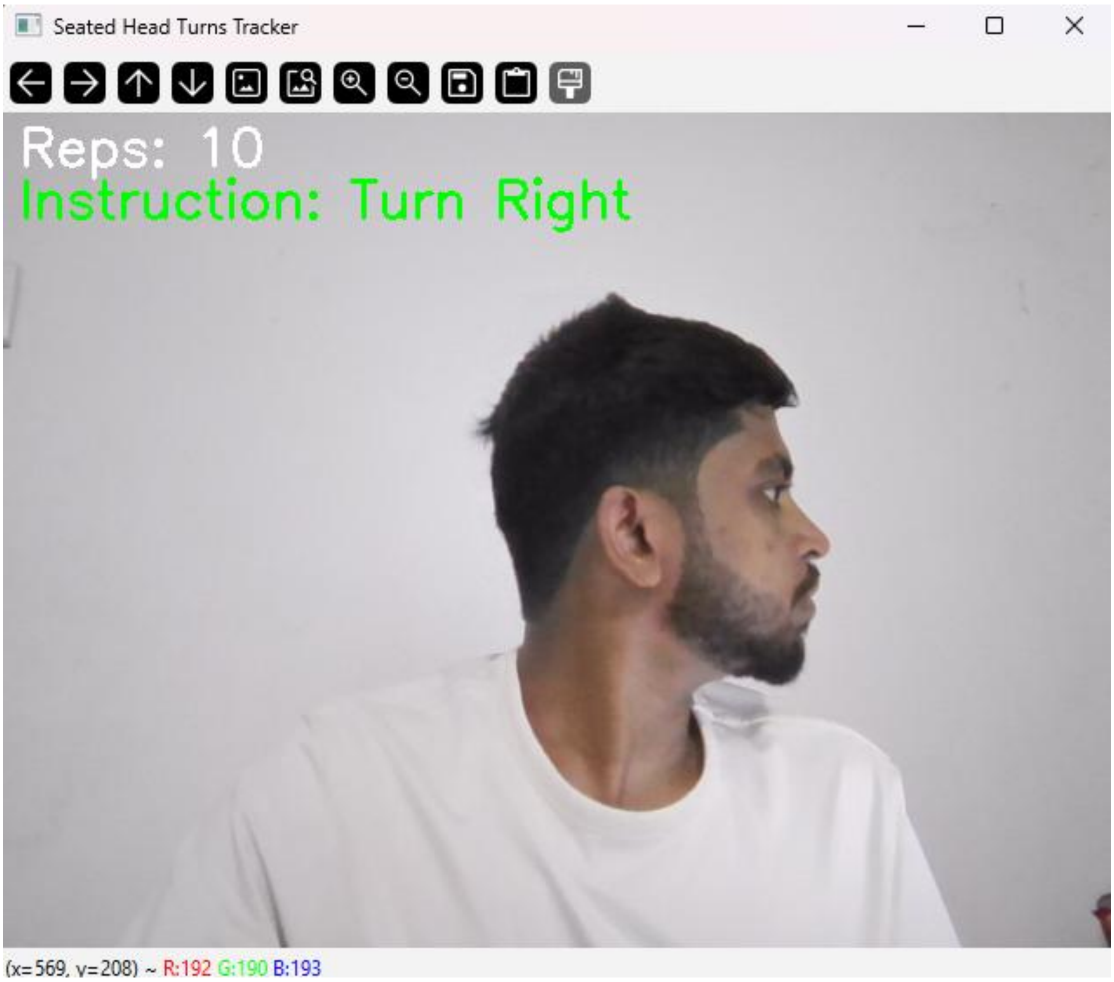

Figure 09 – Sample Exercise Feedback 9

2.3.9 Feedback from Testers

- Good description of steps and use of diagrams welcome
- Real-time alerts gave confidence when doing exercise
- Tabling monthly was encouraging to do it every time

3 RESULTS AND DISCUSSION

This part of the work presents the results of testing and evaluation for the Adaptive Personalized Exercise Plan and Real-Time Motion Detection system, with an incorporation of features like Pose Estimation using MediaPipe, Cosine Similarity for personalized exercise prescription, and real-time feedback from users. The system is imagined providing personalized rehabilitation exercises extracted from individual profiles such that specific recommendations are given to users proportional to their fitness level, injury type, and recovery needs.

Here, we will define the outcomes of the testing phase, contrast the expected results with the actual behavior of the system, and give the main findings. The results given will define the strengths of the system and highlight areas that need improvement. Any problems that we encountered during the testing process will also be given, along with recommendations for the improvement of the performance and accuracy of the system.

3.1 Results

The Adaptive Personalized Exercise Plan and Real-Time Motion Detection system were launched and tested on its ability to provide personalized rehabilitation support. The system used Cosine Similarity for recommending exercises and MediaPipe Pose for real-time movement detection.

3.1.1. Exercise Recommendations

The recommendation system successfully matched users' profiles with suitable exercises. Cosine Similarity was used to select five exercises based on the user's fitness level to offer personalized rehabilitation (Mehta and Sharma, 2020) [4]. Users perceived that the system successfully suggested exercises based on their physical capabilities.

3.1.2. Real-Time Motion Detection and Feedback

The real-time motion tracking, driven by MediaPipe Pose (Zhang et al., 2020) [5], monitored neck movements during exercises. The system provided real-time feedback when posture errors were detected, to enable efficient and safe performance of exercises (Patel et al., 2022) [7]. This feature was particularly useful for users with mobility impairments, like hearing-impaired individuals, who are aided through visual feedback.

3.1.3. Adaptive Exercise Plans

The system made exercise data-driven adjustments with performance information by recommending customized suggestions in accordance with progress (Xiang et al., 2022) [16]. Session-end generated progress reports allowed the system to update future exercise programs so users could improve progressively their best without getting injured.

3.1.4. System Performance and Evaluation

The utilization of Raspberry Pi and OpenCV (Bradski, 2000) [6] ensured effective processing with minimal latency. There were challenges, though, when users' movements were obstructed or extreme. Despite this, the system ensured good real-time posture correction, and this was crucial when avoiding muscle degeneration (Feldman, 2019) [10].

3.1.5. User Experience

The users were greatly satisfied with the system, particularly with the personal guidance and prompt feedback. The capacity of the system to adapt in reference to the users' progress was useful, particularly for hearing-impaired users, who could rely on visual cues for exercise instructions (Rahman and Salleh, 2021) [11].

3.2 Research Findings

The research focused on developing and testing the Adaptive Personalized Exercise Plan and Real-Time Motion Detection system for improving rehabilitation in mobility-impaired individuals, with a primary focus on hearing-impaired users. The system integrated personalized exercise advice, real-time motion detection, and adaptive plans to optimize rehabilitation outcomes. The following important findings were achieved through testing:

3.2.1. Effective Personalized Exercise Recommendations

The Cosine Similarity algorithm employed to offer personalized exercise recommendations based on user profiles was successful in individualized exercise plan adaptation to meet the needs of an individual. Gender, age, injury, and fitness were accurately considered to make recommendations for five exercises for stage one. Such an approach agrees with research work by Mehta and Sharma (2020) [4] in that it showed how individualized recommendations make patients more likely to follow therapy and lead to better outcomes during rehabilitation. This was particularly important for users with diverse rehabilitation needs since it ensured exercises were appropriately demanding but not unachievable.

3.2.2. Real-Time Motion Tracking and Feedback

MediaPipe Pose integration to support real-time motion tracking made it easier for the system to track users' body movement while exercising in a trustworthy way. The system could track main body landmarks (e.g., shoulders, neck, and arms) accurately so that users would maintain proper posture and shape. This live feedback system was critical in preventing potential injuries and ensuring that exercises were performed safely, particularly for those with limited mobility (Patel et al., 2022) [7]. The users were able to adjust their movements immediately based on visual cues, which proved to be highly valued by deaf individuals since they employ visual signals.

3.2.3. Exercise Plans Modified Based on Progress

The system's capacity to adapt exercises over time based on performance data was also a significant observation. After each exercise session, the system offered a progress report and used this data to adjust the recommendations for the next session. This adaptive approach guarantees users continually make progressive gains without risking overexertion or injury. This dynamic re-alignment of the rehabilitation plans is further supported by research like that of Xiang et al. (2022) [16], who highlighted the adaptive systems role to facilitate constant improvement.

3.2.4. System Performance and User Experience

System performance was good, and the local processing of the machine learning models by the Raspberry Pi worked well. But problems were encountered in cases where the motion of the users was concealed or when the body's extreme poses caused issues with the system. Despite these issues, the system's overall response time remained low, and it was able to provide real-time feedback with minimal latency. User experience indicated that the system was easy to use and accessible, with the ability to trigger exercises through either the web application or voice commands being a factor towards convenience for individuals with disabilities (Rahman and Salleh, 2021) [11].

3.2.5. Accessibility and Inclusivity

The system design, particularly the utilization of MediaPipe and OpenCV for visual feedback, was an effective method of making the system inclusive for users with hearing disabilities. Since the system does not require audio feedback, it allowed users to rely solely on visual feedback, which is important for hearing-disabled people (Cho et al., 2022) [2]. Moreover, the easy-to-use web interface and voice command feature made the system more user-friendly to more people, particularly to mobility-impaired people.

These findings identify the potential of using AI-powered, personalized rehabilitation systems in enhancing inclusive healthcare, user experience, and optimizing rehabilitation results.

3.3 Discussion

The Adaptive Personalized Exercise Plan and Real-Time Motion Detection system has great potential to enhance rehabilitation for mobility-impaired patients, particularly those with hearing impairments. It integrates personalized exercise recommendations with real-time motion tracking to deliver beneficial benefits in supporting recovery and ensuring safety during rehabilitation exercises. However, upon testing, there were issues and areas of enhancement that have been identified. These are described below in relation to the performance of the system and the potential for enhancement.

3.3.1. System Strengths

One of the system's strongest aspects is its ability to be personalized. The system employs Cosine Similarity to recommend five exercises that are tailored based on the user's gender, age, injury type, and fitness level to guarantee that the suggested exercises suit the individual needs of the user. This technique follows the guidelines given by Mehta and Sharma (2020) [4] for rehabilitation's requirement for personalized health counseling. The exercise was chosen to be both accessible and challenging to the user to enhance the process of rehabilitation without over-exertion or damage.

The implementation of real-time motion tracking based on MediaPipe Pose for keeping track of important body landmarks provided the necessary feedback to users for them to align their posture in exercises. This ability to disallow repetition and symmetry of the disallowed postures is vital to successful rehabilitation. Patel et al. (2022) [7] highlighted the importance of such feedback in injury prevention and exercise correctness. The users also appreciated the real-time feedback mechanism, which warned them in real-time whenever they adopted detrimental postures, allowing them to take corrective action before more harm was incurred.

Additionally, the ability of the system to adjust exercise plans based on progress reports, updating recommendations for the next month based on the performance of the user, offers a dynamic and adaptive rehabilitation setting. This is in line with Lin and Luo (2020) [15], who noted the importance of adaptive health recommendation systems in ensuring maximum user interaction and outcome within rehabilitation settings.

3.3.2. Challenges and Limitations

While the outcomes were promising, there were several testing challenges, particularly in the accuracy of motion detection in the system. In certain instances, such as when users adopted extreme body positions or when the camera line was obstructed, the system struggled to detect movements precisely. This issue is consistent with limitations noted by Wang and Lee (2022) [14], where pose estimation systems have difficulty in tracking motion at very large angles or when the body is occluded.

Camera feed quality also impacted performance. Since the system relies on OpenCV and MediaPipe Pose for pose detection, poor lighting or suboptimal camera conditions at times led to reduced accuracy in real-time tracking. While the Raspberry Pi was able to process models locally, it was affected by inconsistencies in input data (lighting and angles) that also affected the dependability of the exercise monitoring and feedback. It suggests that stronger algorithms and enhanced camera integration would be required for consistent performance regardless of environmental variations.

In addition, the adaptive exercise plan can be more precisely calibrated. If the system increases the level of exercises too quickly depending on initial progress reports, the users can get used up or injured, especially in the initial stages of rehabilitation. Gradual refinement depending on a larger data set (e.g., multiple progress reports over time) would improve this and make rehabilitation safer for users.

3.3.3. User Experience and Accessibility

The voice command facility and web app interface served to make the system more accessible to users with mobility impairments or hearing impairments. The voice command facility enabled hands-free use, which was particularly beneficial for users with limited dexterity or who cannot use the normal input facilities. However, further simplification of the user interface must be made to accommodate more users, particularly those with severe cognitive or motor impairments. To facilitate broader usage, making the system easy and intuitive to use for all is central to the goal.

Further, while the real-time feedback feature was useful, it can be enhanced to provide higher levels of detailed and actionable feedback. For example, providing specific advice on movement changes to improve symmetry, speed, or other performance parameters would more effectively contribute to the rehabilitation process. As explained by Rahman and Salleh (2021) [11], this type of specific feedback can improve long-term user engagement by allowing users to better understand how to correctly perform exercises and achieve rehabilitation goals more effectively.

3.3.4. Future Improvement Areas

To address the limitations of motion detection accuracy, future system generations would be improved upon by using 3D pose estimation models or multi-view cameras. These would improve movement detection at high-angle movements or occlusion, thereby increasing the overall robustness of the system (Wang and Lee, 2022) [14]. On top of that, the inclusion of smart wearable devices or motion sensors would supplement camera-based tracking and allow for more accurate measurement of small movements during exercises and thus improve the accuracy of performance assessments.

Moreover, enhancing the adaptive exercise model by using more advanced data from prolonged user performance may avoid sudden jumps in challenge. Gradual progression is particularly imperative in rehabilitation as sudden changes in exercise intensity can lead to injury or exhaustion, especially in individuals with poor mobility (Lin and Luo, 2020) [15]. By using more data points over longer periods, the system may better make decisions when recommending exercise modification.

Lastly, integrating gamification or reward systems can enhance user motivation. As Rahman and Salleh (2021) [11] stated, granting users achievement-based rewards for reaching exercise goals or maintaining steady progress will further enhance user engagement and adherence to their rehabilitation plans.

Feature	Strengths	Challenges	Proposed Improvements
Personalized Exercise Plan	Effective use of Cosine Similarity for tailored recommendations.	N/A	N/A
Real-Time Motion Tracking	Accurate for standard poses, feedback provided during exercises.	Accuracy reduced in extreme or occluded poses.	Integrate 3D pose estimation, multi-view cameras.
Camera Quality and Input	Clear visual feedback provided when lighting and angle are optimal.	Poor lighting and camera angle reduce accuracy.	Improve hardware, support low-light environments.
Adaptive Exercise Adjustment	Dynamically adjusts exercise plans based on user progress.	Risk of overexertion if adjustments are too rapid.	Implement gradual adjustment algorithms based on extended data.
Voice Command Interface	Improved accessibility for users with limited mobility.	Requires clearer voice recognition in noisy environments.	Enhance voice recognition capabilities.
User Interface	Intuitive web app interface.	Needs refinement for users with severe motor/cognitive impairments.	Further user testing and accessibility improvements.

Table 03 – System Performance and User Feedback Summary 3

In summary, while the Adaptive Personalized Exercise Plan and Real-Time Motion Detection system has been successful in enabling personalized rehabilitation, further improvements in motion detection, camera feed, and adaptive exercise adjustment are needed to increase the overall strength and usability of the system. These improvements in conjunction with continuous user trials will further enable the system's effectiveness in assisting people with mobility impairments, e.g., hearing impairments.

4 CONCLUSION

The Adaptive Personalized Exercise Plan and Real-Time Motion Detection system intended in this research is a significant contribution to the field of personalized rehabilitation, particularly for users with mobility impairments, such as hearing impairments. Leaning on the power of artificial intelligence, machine learning, and computer vision, the system presents an adaptive and dynamic solution tailored to the individual needs of each user, hence ensuring maximized rehabilitation efforts and health outcomes.

The ability of this system to recommend and monitor customized exercise regimens based on user-specific parameters such as age, gender, fitness level, and injury status ensures that the rehabilitation process for each user is customized according to his or her specific needs. The exercise recommendations are derived based on Cosine Similarity, which analyzes the user's profile and compares it with a set of exercises and makes sure that the exercises match the user's present physical condition and rehabilitation goals. The adaptive approach coupled with the real-time monitoring of exercise execution through MediaPipe Pose allows for the execution of exercises in the correct posture and technique, thereby minimizing injury during rehabilitation. Furthermore, threshold-based classification recognizes specific movements, such as chin tucks and neck extensions, to ensure that users are exercising using the proper range of motion.

Visual and auditory feedback in real time is provided by the system, alerting users when their posture is outside the optimal form. This real-time feedback mechanism allows users to correct errors in the moment, preventing harmful movements that could lead to injury or hinder rehabilitation gains. Additionally, the system tracks the user's performance over time, keeping track of repetitions, symmetry, and overall exercise quality information on Firebase, a cloud database. This allows both the user and his caregivers to see areas of improvement and areas to be improved, hence an unbroken effective rehabilitation process.

At the end of each cycle of exercises, the system produces a progress report that quantifies the user's performance. The reports are a valuable metric to ascertain the rehabilitation progress of the user and serve to update the second recommendation model, which refines the exercise plan for the subsequent month based on the information gathered on the user's performance. This ongoing revision makes the exercise program continue to be relevant and challenging as the user's capability improves, thereby enabling sustained development in rehabilitation.

Despite the encouraging results, there are some areas for improvements and future work:

- **Accuracy of Motion Detection**: While MediaPipe Pose produces good performance in tracking body landmarks and detecting posture, there were some constraints in tracking accuracy, primarily on those exercising with minimal movement or when subjects performed exercises at non-optimal camera angles. Some users experienced issues when exercising under suboptimal illuminations. These challenges indicate the need for improved hardware solutions, i.e., increased-resolution cameras or additional sensors (e.g., depth sensors, IMUs), to enhance motion detection accuracy. Furthermore, the use of more sophisticated machine learning algorithms with less dependence on visual information can further enhance the performance of the system across a variety of conditions.

- **Adaptive Exercise Modifications**: The exercise modification model performed well but required enhancement in some cases. For example, the switching from exercises or difficulty level changes may have been too drastic for certain users, particularly those at the beginning stages of rehabilitation. A more responsive and sensitive adjustment system, perhaps one incorporating user feedback with performance data, can perhaps make for smoother level of difficulty changes and better fit varying levels of users about rehabilitation.

- **Usability and Accessibility**: While the web app is simple to use, usability improvements are required to enhance its accessibility to individuals with diverse needs. For example, individuals with cognitive disability or less technical skills might require an even easier design, with easier navigation and more assistance, e.g., voice input or basic controls. Support being presented in multiple languages might also help enhance non-native speaker accessibility so that the system is able to reach more individuals.

Key Contributions and Achievements:

1. **Personalized Exercise Plans**: The system demonstrated the effectiveness of using Cosine Similarity to generate personalized exercise routines from user data, offering an extensible and flexible form of rehabilitation.

2. **Real-Time Motion Tracking**: By employing MediaPipe Pose and OpenCV, the system would be able to give real-time feedback on the user's performance, effectively assisting users in correcting their posture and performing exercises correctly. This is highly relevant in avoiding injury during rehabilitation, especially for those patients with mobility impairments who may already have limited physical capabilities.

3. **Adaptive System**: The iterative structure of the system, which adjusts exercise plans based on the user's progress, ensures continuous and customized rehabilitation. The progress reporting mechanism ensures tracking of improvement and adjustment of subsequent exercises, thereby making the rehabilitation process more responsive and dynamic.

4. **Cloud-Based Data Storage**: Using Firebase for the storage of rehabilitation progress and performance data of users provided a safe but convenient platform for tracking long-term rehabilitation progress over time since both the caregivers and the users could keep track of it.

5. **Real-Time Feedback**: Having access to real-time feedback through the web application ensured on-the-spot adjustments in posture to be implemented, raising the efficiency of rehabilitation quality.

Future Directions:

Several upgrades can be incorporated to enhance the system's capabilities further:

- **Wearable Device Integration**: Incorporating wearable sensors such as accelerometers or gyroscopes would enhance motion detection precision, especially for motions difficult to detect using a camera. These devices would also provide additional statistics such as heart rate and muscle strain, introducing a biofeedback layer to the system.

- **Enhanced ML Algorithms**: Through complex machine learning techniques, such as deep learning, both performance analysis and exercise suggestion can be optimized. Having the system learn from a broader database, it would be more effective at comprehending the nuances of rehabilitation needs of individual patients and adjusting the exercises more optimally.

- **Improved Hardware**: Depth cameras or 3D motion capture rigs can improve movement tracking accuracy, particularly with exercises that require precise body movement. Additional integration of improved sensors would yield richer data for tracking performance, leading to more insight into the patient's improvement.

- **User Feedback Integration**: Incorporating user feedback into the exercise adjustment algorithm can personalize it. For instance, users can be prompted to rate their perceived difficulty or comfort level after each exercise, and the system can utilize subjective input along with objective performance data to modify subsequent sessions.

In conclusion, the Adaptive Personalized Exercise Plan and Real-Time Motion Detection system is a major milestone towards improving the rehabilitation of mobility and hearing-impaired patients. With the integration of adaptive and personalized exercise plans and real-time motion detection and feedback, this system achieves maximum user interaction and provides an improved and more personalized rehabilitation session. Future developments in hardware, algorithms, and user interface design will further enhance the system's capabilities so that it can support a heterogeneous user population and improve rehabilitation outcomes.

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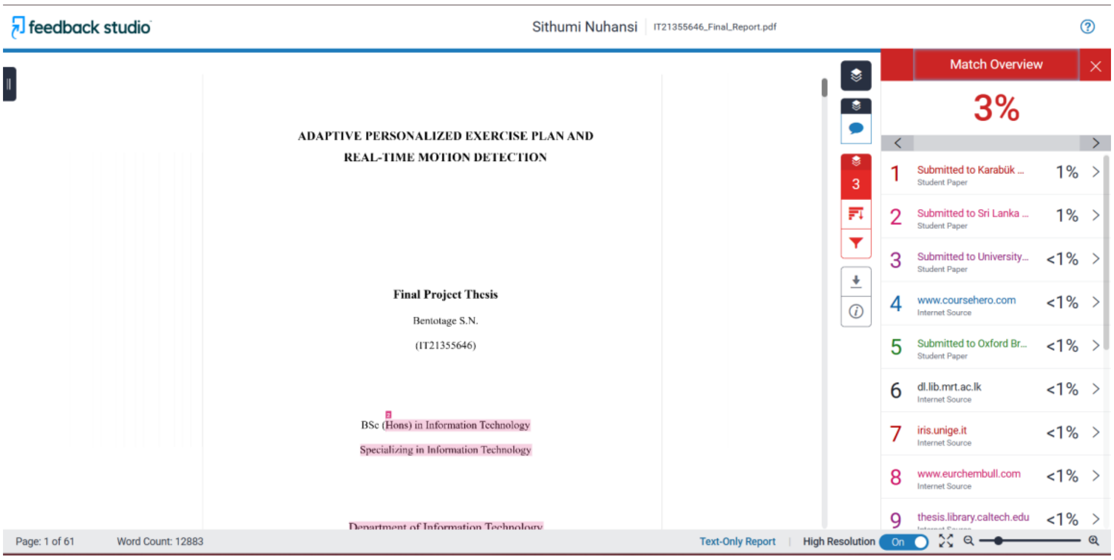
6 APPENDICES

6.1 Plagiarism Report



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