ExerciseCheck: A Scalable Platform for Remote Physical Therapy Deployed as a Hybrid Desktop and Web Application

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ABSTRACT

ExerciseCheck is a scalable, accessible platform designed and developed for the remote monitoring and evaluation of physical therapy. Physical rehabilitation is an important aspect of a patient's recovery from injury and often requires the patient to perform a prescribed set of exercises over medium- to long-term periods. In the absence of a physical therapist, using a low-cost, non-intrusive solution can serve as a complement to in-clinic sessions and provide patients with valuable insights into their exercises. We present the design, implementation, and deployment of ExerciseCheck, a modular system that incorporates machine learning techniques with contemporary web technologies to enable a user-friendly experience for patients and physical therapists. Initially a proof-of-concept, the latest version of ExerciseCheck is now deployed as a hybrid desktop and web application at a Boston University rehabilitation clinic and has been employed by physical therapists in their sessions with individuals with Parkinson's disease. We provide insights into the usability requirements, architecture design, and implementation challenges of the development and deployment of a production-quality platform for remote physical therapy in a clinical setting.

CCS CONCEPTS

• **Human-centered computing** → **Activity centered design; Interaction design process and methods; Human computer interaction (HCI); User centered design;** • **Hardware** → *Sensors and actuators;*

KEYWORDS

Computer Vision, Physical Therapy, Depth Cameras

1 INTRODUCTION

Neurodegenerative diseases such as Parkinson's disease (PD) affect nearly a million people in the United States, and worldwide numbers peak much higher at 6.2 million cases per year [1]. Physical therapy is increasingly being used as a way to treat neurodegenerative diseases [2–4], since since it reduces disability, improves physical function and quality of life. Studies show that individuals

with access to a multidisciplinary physical therapy program have shorter hospital stays, faster recovery periods, and demonstrate more progress on measures of functional independence [5].

Recent advances in physical therapy include exercise gamification [6–8] and use of artificial attachments [9], which are often expensive, uncomfortable, or not sensitive enough to capture all components of a user's movements. On the other hand, depth cameras such as the ones used by the Microsoft Kinect, Intel RealSense, and other off-the-shelf camera systems have gained popularity as low-cost devices that provide data at adequate granularity to assess 3D movement in real time [10–14]. There is also ongoing research which focuses on using deep learning for the prediction and analysis of 3D body posture. [15–18]

In this paper, we describe the development and deployment of ExerciseCheck, an open-source, scalable platform for remote physical therapy that is designed for both in-clinic and at-home use. We have successfully deployed this system in a clinical setting and tested the system with patients with Parkinson's disease. In this paper, we focus on the description of our novel system architecture, deployment strategy and user experience design, while the data analytics for these tests are discussed in detail in our companion paper [19]. Our contributions are based on a new usability requirement analysis. Previously existing applications that make use of the Microsoft Kinect, including a proof-of-concept system we developed previously [20], suffer from various drawbacks; most of them are prototypes not suitable for multi-site use and deployment, and often lack a comprehensive system that can be easily used by physical therapists to personalize and update exercise parameters and configuration details at any time. They have primitive user interfaces [21, 22] and lack streamlined workflows to execute the exercises and access control mechanisms to protect patient privacy. One recent work [23] even suggests providing the platform and some configuration files in a disk to the user, with the users having the responsibility of editing the exercise parameters themselves. Such systems do not scale well because they have limited data persistence capabilities and lack a reproducible deployment workflow, making it unsuitable for longitudinal tracking of a user's progress. Our efforts in the following areas address the above issues:

Usability Requirements. Our user population and intended deployment environment heavily influenced the design of the platform architecture and relevant algorithms for data analysis. In particular, our contributions address privacy concerns, accessibility needs, and major user workflows.

Architecture Design. We employ contemporary web technologies to implement a robust infrastructure and a modular, full-stack application that enables streamlined installation and distribution.

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Figure 1: User interface for recording a practice exercise session. During a practice exercise session, the user sees a comparison view of the previously recorded reference exercise (A) and the user’s real-time practice exercise (B). The repetition counter (C) is updated using the real-time repetition detection algorithm. The data is locally persisted and sent to the server at the end of the session.

ExerciseCheck consists of a customizable user management and back-end system, real-time algorithms for exercise evaluation, and a well-defined data layer for long-term storage and analysis.

Implementation and Deployment. ExerciseCheck consists of a hybrid desktop application (installed on the user’s laptop) and a web application (installed on a server). While the bulk of the functionalities of the platform resides in the web component, it inter-operates with the desktop application to facilitate data transfer between the local data source (such as the depth camera) and the application layer. The web application consists of a robust data pipeline that employs server-side compression techniques to store large volumes of exercise data in a NoSQL database. The remote deployment of the web application allows us to update the platform with new features without having to update each user’s local desktop installation.

2 RELATED WORK AND CONTRIBUTIONS

Initial interest in studying the benefits of including games and physical hardware devices as part of the physical therapy process has been presented more than three decades ago [3, 4]. However, while there is evidence that games have the potential to be powerful motivators for engaging users in physical activity, especially games for clinical or rehabilitation purposes, there is a relatively limited amount of public research [6–8, 24] on the effectiveness of the motion sensing capabilities of commercially available gaming devices. Previously, video games coupled with hardware devices

that track motion have proven useful in assisting with patient recovery, specifically with home-based use [25, 26]. Many physical rehabilitation techniques include additional robotic hardware that needs to be in contact with or worn by the user. An example is a glove device (a hand glove) that can be used for finger and palm or body-wide rehabilitation [9, 27]. Although these systems have been gaining traction and are reported to function accurately, there are some inherent problems: robotic hardware systems are mostly contact-based, can cause discomfort [28] and are a burden to patients with physical injury. Their efficacy may also suffer because of patients’ low motor control or the lack of synchronization between the device and body parts involved [29]. Thus, contact-less rehabilitation techniques using computer vision have become more popular in the last few years [30–32].

The Microsoft Kinect is an example of a portable, contact-less device that is an established and popular choice for rehabilitation platforms [33, 34] because of its advanced capabilities to track joint movement and orientation. Studies show that the Kinect has joint-tracking capabilities which are comparable to existing state-of-the-art tracking systems that involve having a physical contact with the user [11, 35]. The Kinect gives 3D joint coordinates and orientation for 25 joints using an infrared sensor.¹ Usage of the Kinect has shown increased motivation for physical rehabilitation among patients with varying neurological disorders such as cerebral palsy and muscle atrophy [13]. Furthermore, the Kinect’s motion

¹More details about the Kinect and its capabilities can be found at <https://go.microsoft.com/fwlink/p/?LinkID=403900>

Figure 2: User interactions such as the circular target and countdown timer help the user get into position for an exercise. The gridlines and floor plane provide perspective and serve as visual guidelines.

Figure 3: The platform allows the exercise to be tailored to an individual. Physical therapists can set the number of sets, repetitions, and difficulty level of an exercise for a particular patient.

tracking capabilities have been used to evaluate gait abnormality in patients suffering from Parkinson's disease, which is useful in detecting and mitigating fall risk [14].

Prior works [21, 23, 36, 37] mostly rely on standalone software that have not been incorporated into cloud-based environments. This makes installation, distribution, and multi-site use arduous. Some applications offer a convoluted strategy to define and update exercise parameters, such as configuration files defined in the *eXtensible Markup Language* (XML) or direct editing of the game development interface [38]. This approach does not allow exercise parameters such as the joints involved, direction of rotation, and number of repetitions to be updated easily. Other applications have been used as proof-of-concept systems that allow one-time exercise sessions but do not persist data over multiple sessions by the same user, which is necessary for assessing the patient's progress. Most such systems employ a joint-to-joint comparison using values defined statically in the rules of the exercise and do not offer any way to tailor the system to the individual's current exercise level and need. Through development of ExerciseCheck, we address these shortcomings through the following major contributions:

- ExerciseCheck is an efficient, cloud-based rehabilitation platform that is easy to install, update, and distribute in both clinical and home environments.
- Through its user interface, ExerciseCheck allows physical therapists to modify the parameters of the exercise at any point in the treatment plan.
- ExerciseCheck provides real-time feedback to the user regarding both speed and movement accuracy in a simple and intuitive way.

To enable a deep level of personalization for a patient in therapy, we included an innovative functionality that has not been reported in previous systems: Not only can the patient and therapist establish desired movement goals in detail, they can also easily update them when the patient's abilities improve during therapy. ExerciseCheck ensures that the patient's performance during a current exercise is compared to the updated goal rather than an outdated version of the task.

3 SCENARIO AND REQUIREMENTS

In this section, we highlight the scenario that motivated our work and outline usability goals required to implement a scalable, accessible platform for remote physical therapy. We engaged in an iterative process with stakeholders that ultimately informed the user experience design of the platform.

3.1 Application Scenario

For individuals with Parkinson's disease, making regular visits to their physical therapist and following a personalized treatment plan at home can help optimize their day-to-day mobility and improve long-term outcomes [4]. When patients perform exercises at home without the supervision of their therapist, they benefit from learning individualized feedback about their performance that will maximize their exercise program [39]. Receiving feedback through a gamified experience also helps patients become more engaged and motivated, leading to less distractions and often improved performance [40–42].

ExerciseCheck integrates the concepts of telerehabilitation with quantitative evaluation and feedback, empowering patients in their daily exercise and providing physical therapists a data-driven perspective of their patient's progress. We developed a scalable, accessible platform with a minimalist user interface and streamlined deployment process with the following users in mind.

- **Patients:** We worked with individuals with Parkinson's disease and other neurological disorders at Boston University's Center for Neurorehabilitation. Their feedback during the early stages of our design process focused on the value of real-time feedback and visual guidelines.
- **Physical Therapists:** We also collected feedback from physical therapists at the Center for Neurorehabilitation. Their primary goal for a remote monitoring platform was the ease with which one could review patient performance at both an individual and aggregate level. They also emphasized the need for the ability to personalize and update exercises based on patient goals and progress over time. Customizable parameters included selecting relevant joints or direction of

Figure 4: System Architecture

movement, setting the level of difficulty, and changing the number of sets and repetitions (Figure 3).

- **Researchers:** We anticipated this third cohort would benefit from accessing and performing quantitative analyses over exercise data that would improve algorithms and inform treatment plans.

3.2 Usability Requirements

Due to the constraints posed by our application scenario and specific user groups, our platform must satisfy many usability goals. We grouped usability requirements into the following areas: accessibility, privacy, and feedback.

Accessibility. To encourage participation and minimize barriers to adoption, the platform must be easily and rapidly deployable in a number of settings, requiring minimal setup and no specialized knowledge of technology. The user interface of the platform must also be simple to navigate by individuals with low vision and limited mobility and whose technical expertise may only include basic familiarity with web browsers.

Privacy. To enable data analysis without leaking patient data, the platform must enforce different levels of access control and store information about user accounts, exercises, preferences, and exercise data without personal identifiers. By doing so, the platform makes the data available for physical therapists and researchers to evaluate without compromising the privacy of individual patients.

Feedback. To ease users into their exercise routine and inspire long-term use, the ExerciseCheck platform must incorporate user interface elements that provide real-time visual feedback utilizing data from the depth camera (Figure 1). Furthermore, the platform should deliver immediately accessible and jargon-free feedback based on each exercise session to inform users of their progress.

4 USER EXPERIENCE DESIGN

Due to the potential complexity of the ExerciseCheck platform, we engaged in an iterative design process with stakeholders to ensure that we considered functionalities, edge cases, and user experience elements that would be crucial for a production-ready platform. Using the initial proof-of-concept and additional user interface mockups, we met with two patients participating in physical therapy treatment to understand their most immediate needs for improving their daily exercises and to collect their direct feedback on elements that were lacking or could be improved.

Since the platform is intended for both in-clinic and at-home use, we had to consider the variability of environmental setup parameters, including the placement of the depth camera, the angle of the sensor, the distance between the user and the device, and the height of the user. Differences in these parameters affect the capture and display of the motion data. To address this problem, we developed user interactions that inform the user whether they are standing directly in front of the depth camera and at an operational range where the recording of the joint data is reliable.

The other usability challenge was ensuring users have enough time to get into position before starting an exercise. To verify that the user is at an optimal position, a circular target on the screen serves as an alignment field. Initially outlined in red, the target turns green when the user is standing within an operational range from the depth camera (Figure 2). If the positional coordinates (depthX, depthY) of the user's neck lie within the alignment circle, the user is in the correct position. To minimize distractions for the user, the target switches to gray during the recording of the exercise.

When the user is in the correct position, the countdown timer (Figure 2) begins, allowing the user ample time to get into an appropriate posture for the exercise before the recording begins. This timer can be customized based on the user's needs. For additional visual guidance, the user interface also displays gridlines and a floor plane that grounds the user in a more realistic perspective.

Figure 5: Various System Workflows

Using data captured by the depth camera, the platform provides a real-time visualization of the user's movement represented as an articulated skeletal figure. In this paper, we refer to this visualization in two ways: the **"reference exercise"** and the **"practice exercise."** The reference exercise is recorded under the supervision of a physical therapist and represents the personalized standard that the patient must meet based on their best ability to perform that exercise; it can be updated at any time when progress is met or a new treatment goal is established. The practice exercise can be unsupervised and is recorded every occasion a patient performs their exercise program to capture progress on a regular basis.

The platform provides a comparison view of the prerecorded reference exercise and a live view of the practice exercise, so that the patient can aim to perform at the same level as the reference exercise or better (Figure 1). Serving as a personal guide, the reference exercise helps direct the patient's movement, direction, and pace at the level that is optimal for their ability. A repetition counter detects the user's movement and increases as the user completes each repetition. These simple interactions provide the user with enough guidance without overwhelming the user interface and distracting them from completing an exercise session.

When a user completes an exercise session, the platform provides a summary of the user's performance derived from their movement accuracy and speed. Concise and immediate, this summary uses jargon-free language to convey the participant's progress (Figure 6).

5 ARCHITECTURE AND IMPLEMENTATION

5.1 Technology Stack

The ExerciseCheck platform is an open source, full stack hybrid web and desktop application² consisting of four main components: a depth camera, a web server, a front-end web application, and a lightweight desktop application developed with Electron³ (Figure 4). The web application is built using a combination of contemporary libraries and frameworks on top of HTML5, JavaScript, and CSS.

²The platform can be accessed at <https://github.com/ExerciseCheck/>

³<https://electronjs.org/>

It connects to Anchor running on the web server⁴, a highly customizable, open-source back-end user management system. The server includes a NoSQL MongoDB database which is used to persist user accounts, exercises, preferences, and the exercise data for feedback and analysis. The desktop application provides a lightweight wrapper around the front-end web application, and in the process also exposes the computer's USB devices. This provides a bridge between the depth camera (which relays the data locally on the system) and the web for our platform to integrate with the hardware. By reusing the same interface as a website and desktop application, we reduce the development complexity and offer greater flexibility for clinicians who do not have to rely on installed software to manage their patient's data.

For the patient, the ExerciseCheck application can be installed on a computer with network access. The depth camera can be connected to the PC through a USB 3.0 port. The application can be launched the same way as any other executable in the system. For this version of the platform, we use the Microsoft Kinect as the depth camera. The Kinect sensor has a variable frame rate when recording data for both the image sensor (RGB Camera) and the depth sensor (used for skeletal tracking), which depends on the capability of the computer hardware used. Therefore, with sophisticated hardware (such as an Intel i7 gen-2 or higher processor, 8 GB RAM and a USB 3.0 connection), data is generated at 30 fps where each frame generated using the depth sensor contains orientation information and 3D coordinates of all 25 joints. The platform allows for the Kinect to be switched out for any other depth camera available today.

5.2 User Workflows

The user management system has been set up to provide researchers, clinicians, and patients with different levels of permissions within the software. The system has four major user roles: The super administrator (who has root access to create clinicians, analyst and patient roles), the therapists/clinicians (who have assigned patients

⁴<https://github.com/hicsail/anchor>

and can view all data for their patients), the analysts (who have access to only parts of the data), and the patients themselves. The ExerciseCheck work flow (Figure 5) is a multi-step process detailed as follows:

- The super administrator first creates the accounts for the therapist and patient, and then links both of them together. The super administrator can also create an entry for a new exercise and specify parameters that will be used for its analysis, such as the most important joint, the direction of movement, etc.
- The clinician logs into their account and chooses the exercise for the patient. At this stage, they can choose patient-specific settings such as the number of sets and repetitions that need to be performed by the patient, the difficulty level of the exercise, and so on.
- The patient performs a *reference exercise* under the supervision of the clinician. The data for the reference exercise is recorded and saved by the system. This serves as the gold standard for a properly executed exercise (the ground truth) to compare with later exercise sessions.
- Once the reference exercise has been saved, the clinician performs an in-clinic *practice exercise* session with the patient.
- When patients log into the system from the comfort of their home, they will automatically see the exercises for which they have a reference. They can then perform practice sessions at home.
- A real-time repetition detection algorithm keeps track of the patient's motion and counts repetitions performed (as shown in Figure 2). This is discussed in more detail in our companion paper [19].
- At the end of each practice session, the motion information about the most recent practice exercise is sent to the server. The server compares it with the information about the reference exercise, in terms of both speed and accuracy of movement. This feedback is then displayed to the user through the user interface of the application.

5.3 Algorithms and Quantitative Analysis

Normalizing data before analysis. The data analytics component of ExerciseCheck (see our companion paper [19] for details) normalizes the practice data to the reference data before comparison. Each exercise is normalized based on the neck position and then compared against the reference. The depth camera reports the absolute position on the 2D canvas plane. Depending on the moving direction of the exercise, when analyzing the practice exercise, we first either normalize the joint data to body height (calculated as the length between the neck and spine base) if moving in Y axis or by the body width (distance between shoulder left and shoulder right joints) if moving in X-axis. The body height and width are same for each patient, which makes the comparison between the reference and practice exercise signals for a given patient consistent.

Detecting repetitions. One of the major challenges for counting repetitions is the requirement to be fast-responsive and accurate to a set of different difficulty levels and exercises. Since we want the counting to take place on-the-fly, processing the complete set of incoming data from the Kinect data stream is inefficient and

unnecessary. For each exercise, a feature called **"most important joint"** is defined, which is the joint related to the body part that moves the most during that particular exercise. We also define the **"moving direction"** of the exercise which details the axis of most movement. We use the depthX, depthY or cameraZ (depending on the moving direction of the exercise) of the most important joint. We also define the starting direction of the movement when we create each exercise. We calculate and store the minimum and maximum coordinates of the most important joint in the reference, and use that in combination with the difficulty level to define a threshold beyond which a repetition is detected. For example, for an Easy Hand Raise, the threshold will be hit if the moving direction is going up and the current projected coordinate of the user's wrist is at 50 percent of the maximum height reached in the recorded reference. This feature is not bound by the nature of the exercise, as long as the parameters the algorithm requires have been set.

Accuracy and Speed Calculation. For the accuracy analysis, we use a technique called Dynamic Time Warping (DTW) to compare the reference and practice exercise signals. DTW is a technique that is applied to time sequence data and can be used to measure the similarity between temporal segments that vary in their speed. It does so by calculating an optimal match between the two sequences by matching the first, last, and intermediate indices between the data streams [43]. Popular JavaScript libraries for DTW deal with only 1D arrays, while we require data from all the three dimensions for the movement analysis. To solve this we modified the distance definition in the DTW library and used the squared Euclidean distance (in x , y , and z dimensions) as the metric instead. We define the speed as the Euclidean distance between the 3D coordinates of a joint in two consecutive frames and averaged numbers that were above a given threshold. (In that way we excluded the resting periods between repetitions and had more accurate results.) More details about the internal working of the accuracy analysis algorithm are discussed in a separate paper that focuses on the quantitative side of ExerciseCheck [19].

5.4 A scalable data storage layer

When ExerciseCheck records a reference or practice exercise, the frames are temporarily stored in-memory on the client-side before being sent to the cloud server. Each frame occupies roughly 13 KB of space and at 30 fps with sessions lasting several minutes, this data can grow in size very quickly. To overcome this problem, the data on the client-side is first compressed using a JavaScript port of the ZLIB compression library ⁵ and then stored in IndexedDB on the client-side before the user decides to save (or discard) the recorded session. When saved, the compressed data is sent over the network to the cloud server for persistent storage and is further compressed using snappy compression and stored in a MongoDB collection ⁶. Currently, the MongoDB implementation supports a maximum of 16 MB collection size which limits the length of the session stored to roughly 4,400 frames or 2 minutes and 45 seconds of exercise data. With the use of a double compression approach additional CPU time is required for data storage but the results obtained are very impressive. An exercise session of 2 minutes and 45 seconds

⁵<http://nodeca.github.io/pako/>

⁶<https://docs.mongodb.com/manual/reference/glossary/#term-snappy>

Figure 6: After completing an exercise session, the user receives a summary of their performance based on accuracy and speed metrics. A user who performs above average will receive this message for their Accuracy Feedback: "Well done! Your movement accuracy was above average." A user who performs below average will see this message: "It looks like you had some difficulty with movement accuracy."

in length is roughly 60 MB in size which can be compressed to 15 MB prior to persistent long-term storage achieving a 4:1 compression ratio.

5.5 Modular deployment

The system is deployed in a modular fashion. First-time deployment mainly consists of two components:

- A .exe file that comprises of the Electron wrapper and requires a one-time installation on the user's desktop, or can alternatively be provided as a portable file. This executable loads in the web application, which is installed remotely.
- An instance of the web application installed on a HIPAA-compliant server (HIPAA stands for the U.S. Health Insurance Portability and Accountability Act, which regulates electronic use of patient information).

Allowing the bulk of the system to be remotely deployed and updated is beneficial because it enables us to make updates to the functionalities of the system without having to reinstall it on the user's device. When launched, the .exe file always loads the latest version of the web application from the server.

6 EXPERIMENTAL SETUP AND PLATFORM ASSESSMENT

The platform has been tested in a clinical setting with five patients who have different demographics and stages of Parkinson's disease. We ensured that they had a wide Range of Active Motion. The session protocol is as follows:

- First, the clinic staff is trained on how to use the system and its various functionalities.
- Patient training sessions happen weekly. During a session, the user stands 76 cm (30 in) from the wall while the Kinect is placed 330 cm (130 in) from the wall, and 90 cm (35 in) from the floor.
- The therapist explains the procedure and first records a reference exercise performed by the patient for a given exercise.
- For the in-clinic practice exercise session, the patient performs the practice exercise twice, first without looking at

the reference, and then with the option of looking at the reference for guidance.

- Users are asked a tailored set of usability questions so that we can identify sources of satisfaction and areas for further development in the software. Questions range from ease of use to feedback about the interface design and ways in which the platform helps the patients.

All five patients who tried the system found it easy to use, and stated that having the reference exercise shown to them was a useful feature of the software. They mentioned certain features in the user-interface such as the grid lines on the canvas helped them better visualize how high they should raise their foot during the exercise and helped them retain that across sessions. Patients observed that it may be beneficial to display a short explanation about the next step in their exercise so that they do not forget the details of the exercise. All patients liked the repetition counter, and the accuracy and speed feedback provided to them.

7 CONCLUSIONS AND FUTURE WORK

In this paper, we introduced a novel, interactive camera-based system called ExerciseCheck that supports physical therapy and rehabilitation. ExerciseCheck is a lightweight web-based system that offers many functionalities. The same system can be used by both patients and physical therapists. Its modular nature makes it suitable for use both in homes as well as clinics. The system includes support for detecting exercise repetitions and analyzing exercise speed and accuracy. It works for multiple exercises without any modifications. ExerciseCheck is being tested in a clinical setting with Parkinson's patients.

We received feedback from a team of physical therapists who evaluated the feasibility of the platform in terms of design and functionality. Based on their thoughts, the feedback given by the patients during the session, and multiple internal tests, we developed the following plans for future work.

- We are building a feature to allow for concluding an exercise with ease. Currently, the user has to go physically to the system to click the Stop button while performing an exercise,

which introduces extraneous data. We also observed that the evaluation of a user's performance is highly sensitive to the stop time of the exercise. We have implemented two versions of the stopping procedure; one of which includes a virtual stop button that the user can reach via their hands. The second option auto stops the exercise when the desired number of repetitions are completed. We are planning to conduct sessions with existing and new users where we show them both versions to collect their feedback and finalize one version to use.

- We plan to accommodate additional exercises by expanding the number of joints that can be analyzed across our algorithms and data layer. We initially tracked only the joint identified as the critical point of focus for each exercise type. However, with increasingly difficult movements, analyzing a set of joints in relation to each other would improve the accuracy of our real-time repetition detection algorithm and feedback delivery.
- Since the system is used by an elderly population that has a varied level of experience with computer usage, we plan to research and implement an easy yet HIPAA-compliant way of storing session tokens in the platform so that users do not have to worry about forgetting their password.
- We plan to add more features to the user interface such as detailed exercise descriptions, which include what a user should and should not do during a specific exercise, as well as helpful tips while the exercise is being performed.
- In the near future, we plan to conduct sessions in patients' homes where the current version of ExerciseCheck is installed locally. The physical therapist will then login remotely and assess patient performance.

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