Combining Computer Vision and Artificial Intelligence to Support the Rehabilitation of Post-stroke Patients

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Abstract. Considering the rehabilitation needs of stroke patients and the advancements in computational tools within the healthcare sector, this study aims to conduct a comprehensive literature review and develop an application leveraging Computer Vision and Artificial Intelligence to classify movements in support of rehabilitation. To achieve this, a systematic review of relevant literature was conducted, and based on the findings, an application was developed and is currently undergoing testing. Preliminary results from an initial evaluation by a healthcare professional in the rehabilitation field have shown promising outcomes. These findings suggest that tools of this nature can be valuable in enhancing rehabilitation activities and may be further refined to address a broader range of patient needs.

Keywords: Computer Vision · Artificial Intelligence · Motion Analysis · Rehabilitation · Stroke

1 Introduction

A cerebrovascular accident (CVA), commonly referred to as a stroke, occurs when the blood vessels supplying the brain are either obstructed or ruptured, resulting in ischemia and subsequent paralysis in the affected brain region. This condition predominantly impacts men and is among the leading causes of mortality, disability, and hospitalization worldwide. Early diagnosis and intervention in stroke cases substantially increase the chances of a full recovery [13].

Most stroke survivors experience some form of physical or cognitive sequelae. To mitigate the long-term effects of a stroke, affected individuals must have timely access to rehabilitation services that provide comprehensive treatment, addressing their specific needs while considering their capabilities and potential. The World Health Organization (WHO) defines rehabilitation as: "The use of all

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means necessary to reduce the impact of the disabling condition and to enable individuals with disabilities to achieve full integration" [31].

The consequences of a stroke can be addressed in two primary ways: prevention through a healthy lifestyle to mitigate risk factors, and post-stroke rehabilitation, which necessitates multi-disciplinary support and includes various therapeutic interventions, such as physiotherapy for motor sequelae. Physiotherapy plays a crucial role in improving the quality of life for patients affected by these sequelae. Motor physiotherapy specifically enhances flexibility, motor coordination, and mobility, thereby significantly contributing to the functional independence of patients [20].

The integration of computational tools within the healthcare domain has emerged as a significant advancement. Through the use of specialized software, Virtual Reality (VR), and wearable devices, treatments can be personalized, patient progress can be monitored, and autonomy can be fostered, particularly in the context of rehabilitation. This integration of advanced technologies, including Artificial Intelligence (AI) and computer vision, enhances therapeutic efficacy and contributes to an improved quality of life [29].

The global healthcare technology landscape is advancing rapidly, driven by the increasing adoption of digital solutions and smart devices for diagnosing, treating, and monitoring patients. Technologies such as Artificial Intelligence, Virtual Reality, and Telemedicine are revolutionizing healthcare delivery. In Brazil, despite the growing momentum in this direction, significant challenges remain, including unequal access to technology, lack of integration among healthcare systems, and the need for greater investment in research and development [21].

Given these considerations, it is reasonable to anticipate the emergence of new applications aimed at supporting the treatment of stroke patients, particularly in the analysis of exercise performance. This paper presents a study that has thus far encompassed a literature review and the development of an application designed to assist rehabilitation professionals and patients by capturing and analyzing body movements during exercise sessions.

As scientific knowledge advances, computational motion analysis tools are transforming rehabilitation. Through the integration of artificial intelligence, pose estimation, and software engineering, these systems offer in-depth insights into human movement that were previously unattainable.

Accurate data collection and analysis enable researchers to gain a comprehensive understanding of movement patterns, pose estimation, and physiology, facilitating the development of novel rehabilitation techniques. Moreover, the technology empowers therapists to personalize treatments, optimize exercises, and monitor patient progress in real time, enhancing the efficacy of rehabilitation and paving the way for new discoveries in healthcare.

The literature review was conducted in a systematic manner to gain a comprehensive understanding of the research domain in which the proposal is situated and to identify emerging trends and gaps that could inform the development of the application. Drawing on the insights gained from the review and the needs

identified by a collaborating researcher in the rehabilitation field, the application was developed and is currently undergoing testing.

This study is organized as follows: Sect. 2 reviews related work; Sect. 4 provides an overview of the literature review; Sect. 5 details the design decisions and the application development process; Sect. 6 presents the results obtained to date; and Sect. 7 summarizes the findings and concludes the study.

2 Related Work

Researchers worldwide are actively exploring and contributing to the application of Computer Vision and Artificial Intelligence for capturing movements to support the physical rehabilitation of patients.

[11] proposes a supervised learning method for the automatic evaluation of physical rehabilitation exercises, utilizing a Kinect camera and other equipment. According to the author, this approach offers a cost-effective technique for assessing the performance of rehabilitation exercises.

[25] investigates the recognition of human movement actions to analyze movement similarities. This study decomposes the human body into segments represented by combinations of coordinates.

Looking at the research scene in Brazil, we can highlight the use of Virtual Reality in the rehabilitation of stroke patients at the Brazilian Institute of Neuroscience and Neurotechnology (BRAINN). One of their initiatives is the Gesture Collection, a set of Virtual Reality applications that allow interaction through gestures using a sensor, which transforms traditional physiotherapy and occupational therapy activities into more engaging tasks [9].

3 Theoretical Background

3.1 Computational Vision

Computer vision can be defined as the computational field focused on enabling computers to perform vision tasks. It encompasses more than just image capture, which represents only the initial step in a complex process involving noise reduction, region or scene segmentation, information extraction from the analyzed image, and the correlation of images with other images and labels [4].

3.2 Pose Estimation and Human Action Recognition

Human pose estimation is a technique in which a computer aims to detect human movement, with applications across various domains, including virtual cinematography using computer graphics, human behavior recognition, and security systems. The joint positions identified by pose estimation tools may vary due to several factors, such as camera angle, clothing, and contextual elements [19].

Human Action Recognition (HAR) involves the application of video analysis techniques to identify activities performed by an individual through a sequence of observations of the person and their context. HAR systems are designed to automatically analyze and recognize specific human behaviors by extracting knowledge from video data via computer vision techniques. HAR plays a critical role in healthcare, particularly in identifying rehabilitation activities of patients and streamlining processes that were previously manual and reliant on expert judgment. HAR systems must consistently assign the same labels to identical activities, even when performed by different individuals under varying conditions or environments [12].

3.3 Artificial Intelligence

Artificial Intelligence (AI) is a field of Computer Science that seeks to simulate human intelligence through technological means, enabling systems to solve problems, generate solutions, and even make decisions on behalf of humans, thereby enhancing various aspects of daily life. The term "Artificial Intelligence" was first coined by John McCarthy in 1956 during a technology conference at Dartmouth College, USA; however, the concept had already been explored by Alan Turing in 1950, who is widely regarded as the father of computing [30].

The term AI is widely used to describe the latest experiences of interaction between computer systems and their users, eventually becoming an umbrella term that encompasses various computational, mathematical, and statistical techniques. AI is transforming the way people communicate, work, consume, manage their health, plan vacations, and conduct research. It is difficult to find a socio-economic activity that is not mediated by intelligent technologies [18].

Explainable Artificial Intelligence (XAI) is a subfield of AI that seeks not only to deliver outcomes but also to elucidate its own purpose. Such explanations must encompass both the objectives of the system and its decision making process, a feature widely acknowledged as essential for the practical deployment of AI models [6]. Discussions on XAI are becoming increasingly prominent within the technology sector.

Artificial Intelligence in healthcare holds tremendous potential to transform the field, yet its development and application must be guided by ethical, scientific, and responsible principles. Only under these conditions can the technology provide genuine benefits to patients, practitioners, and society at large [10]. In light of concerns regarding trust and transparency in healthcare AI, opportunities for applying XAI in this domain are emerging, aiming to furnish users with insights that extend beyond the mere decision of the model [7,36].

4 Systematic Literature Review

A Systematic Literature Review (SLR) was conducted on the topic, a research method that utilizes existing literature as a data source, offering a comprehensive

summary of the evidence related to a specific strategy. Such reviews are valuable for synthesizing information from targeted datasets [27].

The SLR considered studies published from 2017 up to the date of the search, April 24, 2022, and made available through three databases: the ACM Digital Library, IEEE Xplore, and the CAPES Journal Portal. The automated search feature was used, employing the search string provided below, which was designed based on the combination of the most relevant terms for the research area following several preliminary searches.

Search string: *("deep learning" OR xai OR "artificial intelligence explainable") AND "computer vision" AND ("classification techniques" OR evaluation OR stroke) OR xai methods*

The results and progression of the SLR are summarized in Fig. 1. At each stage, several studies were excluded from the review due to duplication, misalignment with the reviews objectives, or because they were not peer-reviewed articles. After the identification process, abstract screening, and full-text evaluation, 26 studies remained that met all the inclusion criteria and were included in the review.

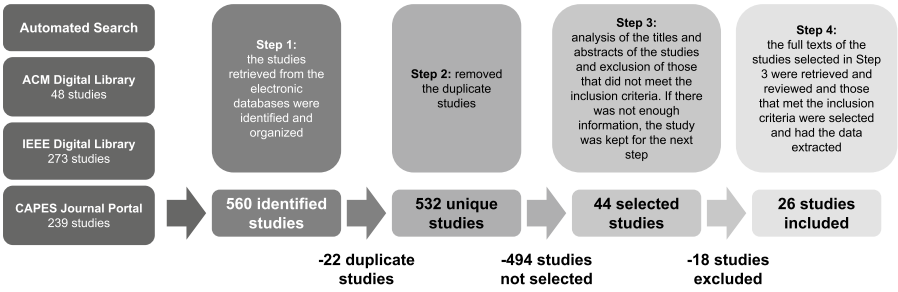

Fig. 1. Overview of the Systematic Literature Review conducted.

4.1 Results

The SLR was guided by several research questions, for which answers were sought. Each question is presented below, along with the corresponding answer derived from the data collected during the review.

In response to the question, "What type of capture do you use?", it is often impractical to deploy sensors in domestic environments. However, it is already common for doctors to record videos during physical examinations using commercially available camera equipment. Recent advancements in deep learning-based pose estimation enable systems to extract features from video recordings [26]. In the computer vision literature, various methods exist for analyzing video data to estimate joints and skeletons. Technologies such as infrared cameras with body markers offer more accurate results but rely on costly systems that are unaffordable for many clinicians and researchers [23].

Table 1 lists the papers according to the capture method cited. It can be observed that video capture was present in the majority (65%) of the papers, followed by the use of sensors, which appeared in 30

Table 1. List of papers according to the capture method used

Authors	Method
[25]	Video
[2]	Video
[39]	Video
[35]	Video
[11]	Video
[26]	Video
[23]	Video
[1]	Video
[19]	Video
[28]	Video
[15]	Video
[38]	Video and sensor
[14]	Video and sensor
[3]	Sensor
[33]	Sensor
[34]	Sensor
[37]	Sensor
[32]	Images
[17]	Images
[19]	Images

In response to the question, "Dataset authorship - own or third-party?", regarding datasets for movement classification, the availability of large-scale datasets is limited, and there are few human movement datasets available for use in rehabilitation-related tasks [8,25].

Finally, in response to the question, "Which programming languages were chosen?", 90% of the authors used the Python programming language in their studies. Table 2 presents the authors who reported the programming language and specifies which language was selected.

4.2 Research Trends in the Field

Based on the results, it can be observed that the majority of authors use pre-existing datasets, with camera capture being the most commonly used method, and Python being the most frequently used programming language among researchers.

Table 2. List of articles according to programming language used

Authors	Programming language
[3]	Python
[38]	Python
[39]	Python
[11]	Python
[14]	Python
[34]	Python
[19]	Python
[37]	Python
[32]	Python and Matlab
[23]	Matlab

The briefly presented SLR is important for guiding this study, as it helps identify trends and gaps in the research area.

5 Development

To ensure continuity in line with the results of the SLR, we made the following decisions:

- Video motion capture, without the need for specialized sensors;
- Development of the application using the Python programming language; and
- Use of an existing dataset, opting not to create a new dataset in order to expedite the development process.

Based on these decisions, an application was developed that allows the professional in charge of the rehabilitation sessions to select the joints, parameterize the movements, and monitor their progress individually per patient.

The main actions that can be performed in the application are described below, outlining the pipeline of activities that will accompany the rehabilitation session.

The joints are obtained using the Mediapipe computer vision and AI library, which employs convolutional neural networks in each video frame to estimate joint positions, thereby generating pose estimation data. The video is captured using a conventional RGB camera (webcam).

5.1 Movement Registration

The process begins with registering the movement. During movement registration, the name of the movement and two sets of joints must be provided. The first set of joints will be used to define the expected angle of the movement, while the second set will be used to calculate a compensation angle for the movement.

The application defines the expected angle of movement as the primary angle that should be generated by the amplitude of the affected limb during a specific movement. The compensation angle is defined as the angle that should not be formed by the joints during the movement. Both angles can be used by the health professional responsible for the motor rehabilitation process to monitor the patients progress during the sessions. The joints supported by the system include the head, left shoulder, left elbow, left wrist, right shoulder, right elbow, right wrist, left hip, left knee, left ankle, left foot, right hip, right knee, right ankle, and right foot.

5.2 Parametrization of Angles

To provide a generic application that accommodates various movements and meets specific demands depending on each patient—for example, analyzing movements of the upper limbs, lower limbs, or trunk—the health professional responsible for the motor rehabilitation process can parameterize two segments of straight lines that must share the same origin in order to form an angle. This will represent the angle of the movement according to the following criteria:

- Point O - This will be the vertex (x2,y2), the starting point of the two line segments;
- Point 1 - This will be the end of line segment A (x1,y1); and
- Point 2 - This will be the end of line segment B (x3,y3).

This is what you get:

$$Vertex = O$$

$$Sides\ of\ angle = \overline{OA}, \overline{OB}$$

$$Angle = A\hat{O}B$$

Figure 2 illustrates the angle formation in an avatar. The area colored in blue represents the angle (A$\hat{O}$B) formed at vertex O during the movement, considering the line formed by the patients arm (black line - side OA) and the line formed by the patients torso (green line - side OB). This represents the desired angle in the movement, with its amplitude being the key measure of interest that should evolve as the rehabilitation sessions progress.

5.3 Session Recording

Once the movement has been registered and its angles parameterized, the session to be performed can be recorded. The healthcare professional responsible for the motor rehabilitation process must select the registered patient and the movement, after which the recording process can be initiated. Upon initiation, the computer's webcam will be activated. It is recommended that the patient stand approximately two meters away from the device capturing the video. When

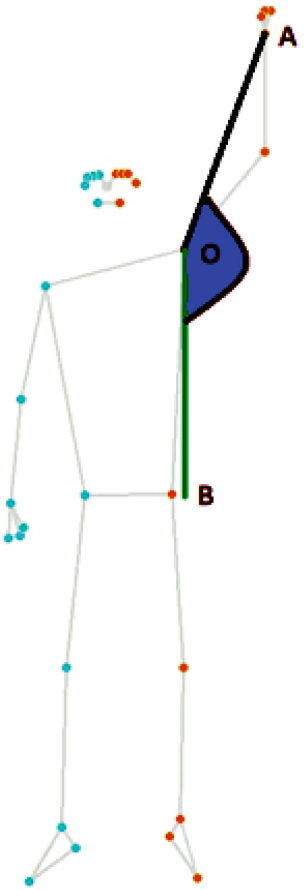

Fig. 2. Angle formation in a movement.

the webcam is activated, the recording does not begin immediately. Instead, the detected body points are first displayed in real-time on the application, and the recording starts once the user clicks the "Start Video" button. This recording setup was designed to allow the patient to view their projection on the system screen and receive initial instructions for performing the movement.

There are also two options available that serve to graphically demonstrate the two angles formed by the movement. Figure 3 illustrates the "right arm lateral raise" movement, where the green polygon represents flexibility (the expected angle) and the red polygon represents spinal compensation (the compensation angle).

Figure 3 shows the application interface, which allows the selection of the patient and movement, as well as controlling the recording process. At the bottom of the window, the camera feed is displayed, overlaid with the obtained data: joint positions and angles.

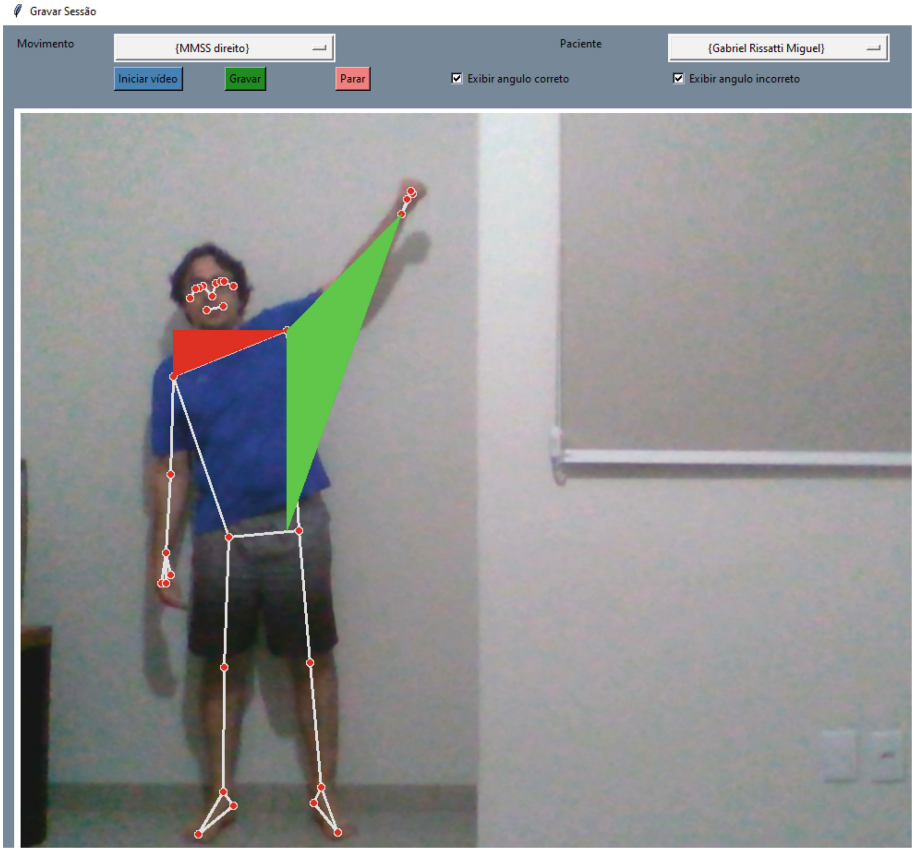

Fig. 3. Recording a session.

The MediaPipe AI framework was used to detect body points, eliminating the need to train a new AI model for this purpose. Training a new model requires a large dataset and access to specialized hardware to achieve adequate performance. Solutions like MediaPipe streamline the development process, enabling a stronger focus on the specific characteristics of the application context while providing easier access to modern technologies [22].

MediaPipe is designed for Machine Learning (ML) professionals, including researchers, students, and software developers, enabling them to quickly implement production-ready ML applications [22]. Among its packages, this study used the Pose Landmarker, which allows the detection of human body landmarks in images or videos [16].

The [24] computer vision library is used to draw the polygons in real-time during the session. At the beginning of the recording, in each video frame, two items are registered in the application: one containing the body points and the other containing the generated angles.

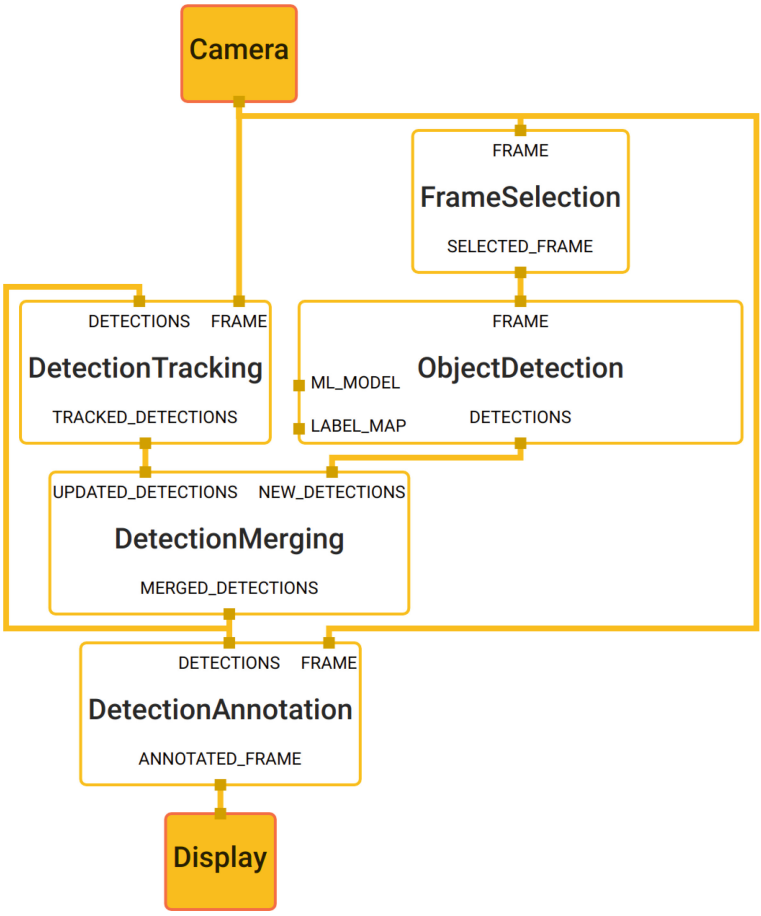

Fig. 4. Object detection using MediaPipe. [22].

The diagram shown in 4 illustrates the internal steps performed by the MediaPipe library, which are detailed below:

- FrameSelection: Enables the selection of the most relevant frames for processing, optimizing performance and reducing computational load.
- ObjectDetection: Utilizes machine learning models to identify objects within a frame. The choice of model depends on the complexity of the task and the types of objects to be detected.
- DetectionTracking: Tracks objects over time, allowing for the analysis of their movement and interactions. This is crucial in applications such as people tracking, behavior analysis, and human-computer interaction.
- DetectionMerging: Combines detections from various sources, including objects and trajectories, enhancing the systems robustness and accuracy

– DetectionAnnotation: Visualizes detections overlaid on the original frame, facilitating result interpretation and system debugging.

6 Results

The results obtained from the development and initial testing of the application are presented below, highlighting the features available to the rehabilitation professional. Once the sessions are recorded, the healthcare professional can analyze the angles generated in each session both individually and collectively.

Figure 5 shows the graph in which the professional can visualize the angles generated during each patient session over time. In this example, the movement performed was the right arm lateral raise, repeated three consecutive times. The blue line represents the arm elevation measurement (expected angle), while the orange line represents the angle generated by spinal curvature (compensation angle).

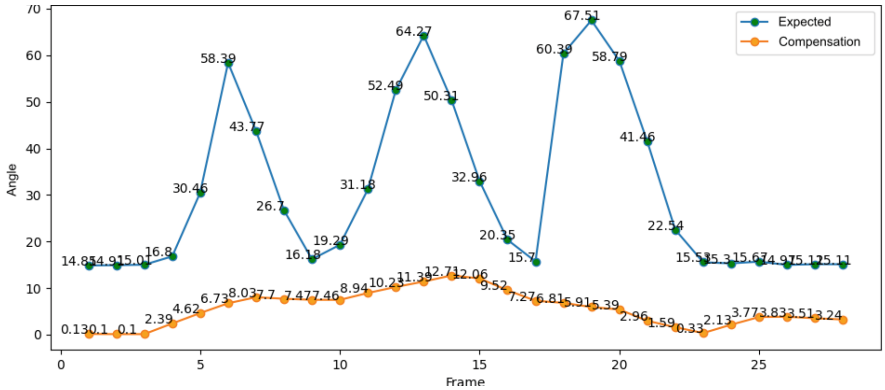

Fig. 5. Individual session analysis.

Figure 6 illustrates the progress of the patient over several sessions. In this example, the patient has completed four sessions. The blue line represents the maximum expected angle for the session, while the orange line represents the maximum compensation angle. This allows the professional to analyze the patient progress across various aspects, such as flexibility and undesired movements.

Another feature available is the ability for both the patient and the healthcare professional responsible for the rehabilitation process to watch the sessions using an avatar generated jointly with the Mediapipe and OpenCV libraries, as shown in Fig. 7, which illustrates the session visualization.

Finally, the system also allows the captured coordinates to be sent to the Rebase repository [5] to enrich the repository and contribute to future research.

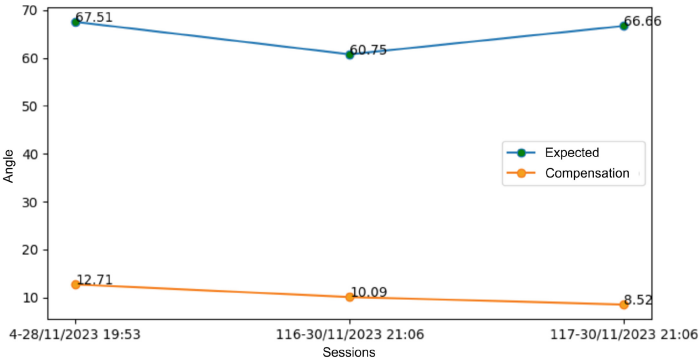

Fig. 6. Playback of a session.

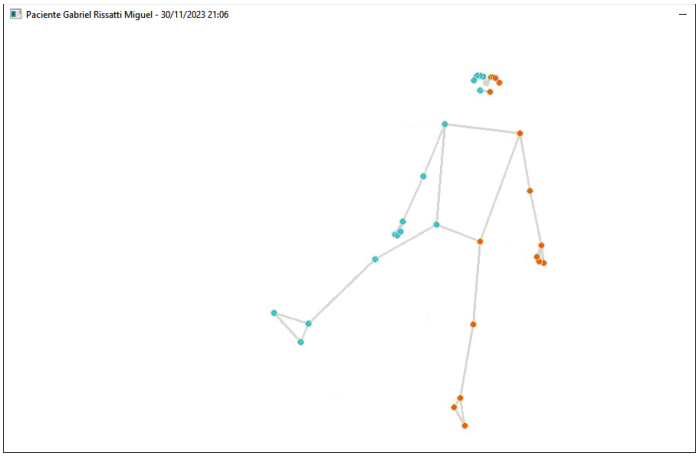

Fig. 7. Playback of a session through the avatar.

Figure 8 illustrates the steps taken during the execution of the application. The execution process can be divided into four stages: data acquisition, data processing, real-time display, and subsequent analysis, with each stage represented by a block.

The operating steps of the application perform the following functions:

- Data acquisition: The rehabilitation session is conducted by positioning the healthcare professional in front of the video capture device.
- Data processing: The captured video is processed using the OpenCV computer vision tool, and pose estimation is performed with the support of the MediaPipe library.
- Real-time display: The application interface displays the captured video, estimated pose, and calculated angles in real time.

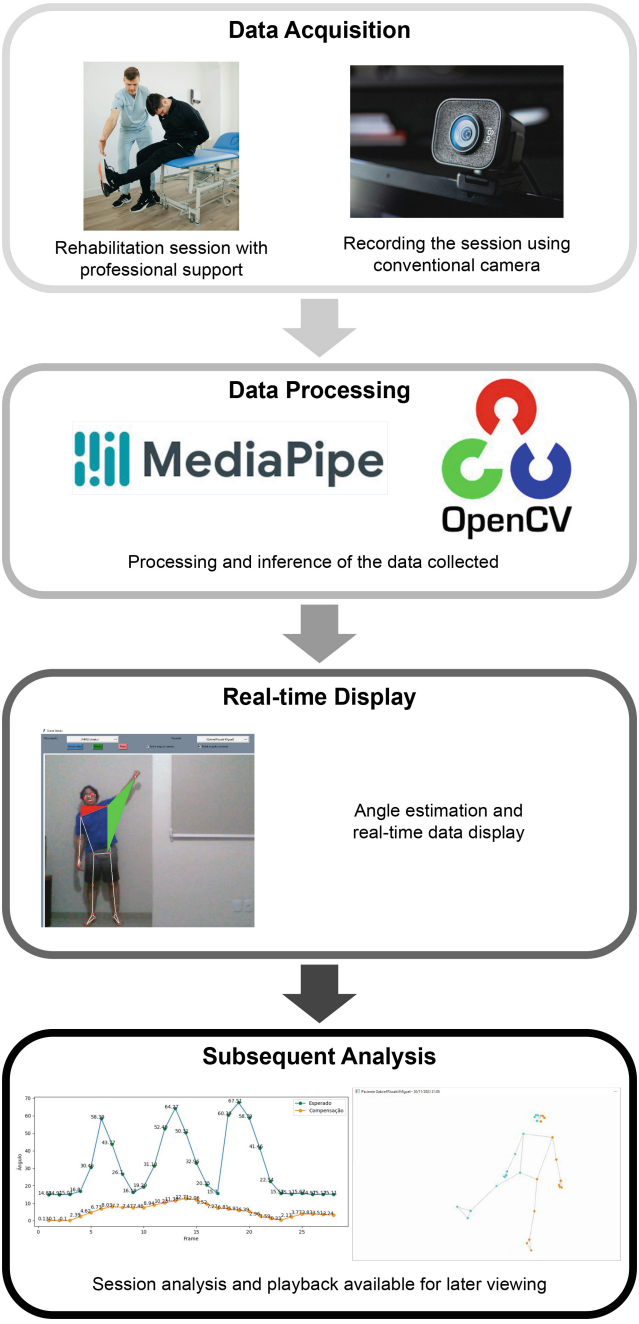

Fig. 8. Application execution steps.

– Subsequent analysis: The obtained data is stored and can later be analyzed using graphs, with the option to replay the session using the avatar.

Although the application is still in the testing phase, the stages encompass the entire initial proposal, aiming to support the rehabilitation process.

7 Conclusion

This study aimed to develop a technological tool to assist in the rehabilitation process of stroke patients. By analyzing body movements during exercise sessions, the proposed application seeks to support professionals in the field, offering more personalized and efficient treatment.

It is considered that the study conducted on SLR and the development of the application have proven relevant to the research area, as evidenced by the evaluation, albeit informal, conducted by rehabilitation professionals. The application is still at the prototype stage but includes the key features initially planned.

To continue this study, we plan to evolve the application by developing and enhancing features based on feedback from the rehabilitation professionals conducting the tests. Once the application reaches maturity, the goal is to expand its use with a group of healthcare professionals and plan a formal evaluation process in a real-world setting, supervised by the professionals, while adhering to all ethical standards and patient privacy requirements, in alignment with the initial objective of supporting the rehabilitation process.

In the future, several beneficial outcomes are anticipated, including detailed analysis of patients movements, enabling the identification of dysfunction patterns and monitoring of progress over time. Additionally, real-time feedback during exercises is expected to be possible, aiding in posture correction and improving motor coordination.

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