ASEAN
Journal of Scientific and Technological Reports
Online ISSN:2773-8752

Research article

Physiotherapy Assistance for Patients Using Human Pose Estimation With Raspberry Pi

Khasim Vali Dudekula[1], Mukkoti Maruthi Venkata Chalapathi[2], Yellapragada Venkata Pavan Kumar[3], Kasaraneni Purna Prakash[4], Challa Pradeep Reddy[5*], Dhiren Gangishetty[6], Manaswita Solanki[7], and Rohith Singhu[8]

[1] School of Computer Science and Engineering, VIT-AP University, Amaravati 522237, Andhra Pradesh, India
[2] School of Computer Science and Engineering, VIT-AP University, Amaravati 522237, Andhra Pradesh, India
[3] School of Electronics Engineering, VIT-AP University, Amaravati 522237, Andhra Pradesh, India
[4] Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, 522502, Andhra Pradesh, India
[5] School of Computer Science and Engineering, VIT-AP University, Amaravati 522237, Andhra Pradesh, India
[6] School of Computer Science and Engineering, VIT-AP University, Amaravati 522237, Andhra Pradesh, India
[7] School of Computer Science and Engineering, VIT-AP University, Amaravati 522237, Andhra Pradesh, India
[8] School of Computer Science and Engineering, VIT-AP University, Amaravati 522237, Andhra Pradesh, India
* Correspondence: pradeep.ch@vitap.ac.in

Abstract: In this work, we employed a device that utilizes Raspberry Pi 4, a camcorder constituent, and a set of audio apparatus to provide real-time assistance to patients during rehabilitation exercises. A person's lifestyle and physical activity explicitly influence their cerebral health. Exercise routines are crucial for maintaining a proper hormone level and physical fitness. Therefore, the workout routine must be constantly examined and adjusted if any changes are needed. With the help of this device, patients may perform their exercises without a physiotherapist. A physiotherapist can show how to perform the exercises during the first few appointments; after that, the patient can utilize the system to track their routines. This will prevent injuries caused by performing exercises inaccurately when not under the guidance of a medical practitioner. The device monitors how frequently a certain exercise is performed and guides the patient in performing the exercises correctly, promoting quicker recovery. The voice generated also helps the patients analyze and correct the exercises if needed. When detecting a slump, an alarm is triggered to alert the individual. We focused on human pose detection using the OpenCV and MediaPipe libraries to capture and dissect in real-time accurately. OpenCV and MediaPipe libraries were used to capture and detect poses accurately in real time.

Keywords: Camcorder; OpenCV; Physiotherapy; Raspberry Pi 4; Real-time assistance; Voice generation

Citation:
Dudekula, K.V.; Chalapathi, M.M.V.; Kumar, Y.V.P.; Prakash, K.P.; Reddy, C.P.; Gangishetty, D.; Solanki, M.; Singhu R. Physiotherapy assistance for patients using human pose estimation with raspberry pi. *ASEAN J. Sci. Tech. Report.* **2024**, 27(4), e251096. https://doi.org/10.55164/ajstr.v27i4.251096

Article history:
Received: September 28, 2023
Revised: June 28, 2024
Accepted: June 29, 2024
Available online: July 11, 2024

Publisher's Note:
This article is published and distributed under the terms of Thaksin University.

1. Introduction

Due to the present development and popularity of Virtual and Augmented Reality, human pose estimation technology is expanding quickly. Numerous applications, such as human-computer interaction, activity detection, motion analysis, augmented reality, sports and fitness, and robotics, have made use of human posture estimation [1]. Multifarious therapeutic treatments are accustomed in the medical specialty of physiotherapy to treat deformities, diseases, and injuries. These methods include massage, heat therapy, exercise, and electrotherapy. In the process of recovering from serious injuries or surgeries, people typically turn to physiotherapy, and they attend the sessions to get rid of the discomfort that limits their strength and movement. Our goal is to incorporate the idea of human position estimates with physiotherapy. This simple-to-create and simple-to-use gadget monitors a patient's movement as they carry out physiotherapy exercises. Based on the input provided, the system considers the coordinates of a body part during an exercise and counts the instances in which a certain movement is recorded [2]. According to medical data, there are just 0.59 physiotherapists for every 10,000 people in India [3]. There is a significant necessity for physiotherapists in India. The thrust for assistance while carrying out therapies is the need of the hour and will be highly appreciated. The need and urge for proper posture maintenance has also surged among people due to the rise in cases of musculoskeletal problems [4]. During the pandemic in 2019, people had no choice but to work from home and they suffered from postural problems [5]. People have suffered from numerous disorders [6] because they have been forced to sit at their desks for long hours while working. The Raspberry Pi is as small as a credit card and is an inexpensive single-board computer [7]. Its compact size and low power consumption make it suitable for portable applications such as wearable devices for human pose estimation. The Raspberry Pi is equipped with a powerful GPU and CPU that can manage the image processing tasks required for human posture evaluation. It is suitable for real-time applications since it can effectively process pictures or video streams from cameras. The Raspberry Pi has a variety of connectivity choices, such as USB, Wi-Fi, and Bluetooth, allowing integration with cameras, sensors, or other devices required for human posture estimation jobs. With this versatility, unique setups can be made to meet certain pose estimation needs [8]. A 30 MP camera was used and was instrumental in capturing high-resolution images and video streams for estimating human pose. Due to the high quality of the images, it was straightforward to identify and analyze important details and landmarks connected to human positions. Ground-truth validations [9] and recordings were done in line and processed by the frameworks as mentioned earlier.

1.1 Related Work

This microscopic comprehension of contemporary contributors describes the recent developments in the said area. Numerous individuals are ignorant of Therapeutic treatment since COVID-19 is under lockdown. To address this issue, Yeo et al. developed a real-time posture sensor for mobile activity using the Body Discovery package. The Flutter SDK and the Dart programming language were used to produce the operation. They showed its utility by precisely recognizing the stoner's position [10]. Nishchal et al. proposed a vision-based human fall detection system The Raspberry Pi and the YOLO algorithm, which defines a computer vision system, are used in this exploration to develop a mortal fall discovery system. The input is a real-time videotape captured by a camera. This technology has the potential to enhance the well-being of older adults and individuals with disabilities by offering safety and security measures, thereby improving their overall quality of life. To identify the human fall, they employed the YOLO method, Alpha-pose estimation, and ST-CGN skeletal pose action recognition [11]. Gregory et al., on the other hand, focused on a new gamified recovery system for those who have had total knee replacement surgery that uses a dereliction detector placed on the knee. When a case detects activity, a one-of-a-kind, single-light, moveable, and extremely low-cost detector with an Inertial Measurement Unit, IMU is mounted to the case's bottom leg to capture its exposure in space in real-time [12]. By using the Raspberry and Pose Net models, Kosei et al. proposed a human posture recognition system involving a single-board computer, and a posture recognition system was created. Their approach uses the disguised Pose Net model to identify several important body parts from the camera module. The proposed system may recognize six different postures and four different movement types [7]. The proposed approach for assessing yoga positions utilizes disguise discovery to help individuals in tone-literacy yoga. The system begins by relating a yoga disguise using a multi-part discovery from the PC camera. Later, it calculates the variation in body angles. However, Maybel et al.'s system provides corrective feedback if the difference exceeds a destined threshold [13]. Navjot et al. focused on the edge device grounded on the Raspberry Pi, the Mini-Xception Deep Network, due to its superior computational effectiveness, allowing for faster processing compared to other networks. This device has successfully achieved a 100-delicacy rate for real-time face discovery, surpassing the delicacy reported in the state-of-the-art approaches using the FER 2013 dataset by reaching 68 delicacies [14]. By exercising a coral USB accelerator, Ryberg et al. successfully linked and navigated toward a specified object, flaunting effective performance across all tested control systems using the Raspberry Pi. This opens up possibilities for exploring the eventuality of real-time object identification in briskly-paced scripts [15]. Raspberry Pi-based sleep posture recognition system using an AIoT technique by Pei-Jarn. The study introduces an IoT-grounded sleep monitoring system that operates without physical contact, exercising a Jeer Pi 4 Model B and RFID markers bedded in bed wastes. This low-cost and energy-effective microsystem incorporates a Random Forest Bracket (RFC) to identify different sleep positions. The sleep position data is also transmitted via Wi-Fi to a garçon database and displayed on a computer [16].

1.2 Paper Contribution

From the above-described literature works, it is observed that several papers discussed different applications of human pose estimation using various algorithms and frameworks. There has been no such work that presents real-time and quality physiotherapy assistance to patients. Further, lightweight technology like Raspberry Pi wasn't being used for the processing of all the landmarks on the human body. With this motivation, this paper proposes a system that uses body landmark detection frameworks: MediaPipe and OpenCV to accurately capture the exercises being performed by the users and provide guidance.
The major contributions of the proposed work can be summed up as follows.

- The frameworks were modified, and new models utilizing MediaPipe, OpenCV, and PyGame were created and applied on live video streams as well as pre-captured video data.
- These models provide a count of the exercise and in addition to this, a proper system will guide the users at home through audio and visual feedback.
- This process was performed based on the average joint angles calculated and based on the matching of these angles, filtering was done and output was given.

The remaining sections of the paper are organized as follows. Section 2 presents the description of the datasets that are used in this paper. Section 3 presents the description and implementation of the proposed methodology. Section 4 presents the comparative results and discussion between the methods used and other existing frameworks. Section 5 summarizes the outcomes of the paper. It also mentions the proposed work's limitations and potential future directions.

2. Description of Datasets

Datasets of participants performing various physiotherapy exercises related to spinal exaggeration and cardiovascular fitness. The dataset included both recorded videos and real-time video streams captured through the camera module.

- Uploading pre-recorded videos: Participants could upload previously recorded videos of themselves performing the exercises.
- Live camera feed: Participants could opt to use the live camera feed from the camera module to perform the exercises and have real-time feedback.

The two different kinds of data put to use for developing the models are described in sections 2.1 and 2.2.

2.1 Pre-recorded video data

The pre-recorded video data is sourced from the University of Idaho's Physical Rehabilitation Movement Data (UI-PRMD) collection. This freely available dataset contains movements associated with common exercises performed by patients in physical rehabilitation programmes. For data collection, ten healthy volunteers repeated ten different physical therapy motions. Motion was captured using a Vicon optical tracker and a Microsoft Kinect sensor, which provided the locations and angles of all full-body joints. This dataset provides a solid foundation for the mathematical modeling of therapeutic movements and for creating performance metrics to assess patient consistency in carrying out prescribed rehabilitation activities [17]. Using this professionally gathered dataset ensures the quality and reliability of our ground truth data.

2.2 Live-camera feed

Video capture option is enabled and the user's video is used to capture the various landmarks. This is being done using a camera module that is connected to the Raspberry Pi directly for fast execution.

The details of five different users and the exercises being performed by them in the case of pre-recorded videos are given in Table 1. The columns related to the data are 'User ID', 'Exercise Performed', 'Area of issue', 'Duration of exercise', and 'Video'. The column 'Exercise Performed' depicts the name of the exercise the respective user is performing, and 'Area of issue' represents the region of the user's body or part that requires physiotherapy assistance. The time spent by the user on any exercise is given in the column 'Duration of exercise'. The column related to the video data is 'Video' which holds the videos of exercises of the user.

Table 1. Description of recorded video data.

User ID	Exercise Performed	Area of Issue	Duration of exercise	Video
1001	▪ Partial Curl	▪ Spine, hip, neck	▪ 73s	▪ user1pc.mp4
	▪ Bridge	▪ Heart, knee, hip	▪ 102s	▪ user1b.mp4
	▪ Shoulder rolls	▪ Shoulder, heart	▪ 83s	▪ user1sr.mp4
	▪ Squats	▪ Spine, hip, knee	▪ 31s	▪ user1sq.mp4
	▪ Back extension	▪ Hip, spine	▪ 40s	▪ user1bck.mp4
1002	▪ Push Ups	▪ Heart, upper arm	▪ 17s	▪ user2pus.mp4
	▪ Squats	▪ Spine, hip, knee	▪ 35s	▪ user2sq.mp4
	▪ Bird dog	▪ Spine, knee, hip	▪ 42s	▪ user2bd.mp4
	▪ Back extension	▪ Hip, spine	▪ 33s	▪ user2bck.mp4
	▪ Bridge	▪ Heart, knee, hip	▪ 85s	▪ user2b.mp4
1003	▪ Shoulder Rolls	▪ Shoulder, heart	▪ 95s	▪ user3sr.mp4
	▪ Bridge	▪ Heart, knee, hip	▪ 120s	▪ user3b.mp4
	▪ Squats	▪ Spine, hip, knee	▪ 80s	▪ user3sq.mp4
	▪ Back extension	▪ Hip, spine	▪ 61s	▪ user3bck.mp4
	▪ Cat-cow stretch	▪ Spine, shoulder	▪ 72s	▪ user3cw.mp4
1004	▪ Partial Curl	▪ Spine, neck, hip	▪ 26s	▪ user4pc.mp4
	▪ Bird dog	▪ Spine, knee, hip	▪ 33s	▪ user4bd.mp4
	▪ Back extension	▪ Hip, spine	▪ 18s	▪ user4bck.mp4
	▪ Shoulder rolls	▪ Shoulder, heart	▪ 21s	▪ user4sr.mp4
	▪ Squats	▪ Spine, hip, knee	▪ 13s	▪ user4sq.mp4
1005	▪ Bridge	▪ Heart, knee, hip	▪ 36s	▪ user5b.mp4
	▪ Shoulder rolls	▪ Shoulder, heart	▪ 45s	▪ user5sr.mp4
	▪ Cat-cow stretch	▪ Spine, shoulder	▪ 28s	▪ user5cw.mp4
	▪ Bird dog	▪ Spine, knee, hop	▪ 60s	▪ user5bd.mp4
	▪ Push Ups	▪ Heart, upper arm	▪ 24s	▪ user5pus.mp4

3. Description and Implementation of the Proposed Methodology

OpenCV was utilized for video capture, image processing, and visualization of results and MediaPipe was used to detect the important body landmarks.

3.1. Mediapipe Framework

The posture estimating abilities of the MediaPipe framework can be used to detect exercises. The shoulders, elbows, wrists, hips, knees, and ankles are just a few of the body joints that may be estimated using the MediaPipe Pose model in 2D. Exercise patterns and motions can be identified by tracking the spatial correlations and movements of these key points throughout time. This framework can be used to represent several elements of a perceptual pipeline graphically, such as model inference, media processing algorithms, and data conversions [18]. The values from all the modalities are optimally merged during the pipeline process. Also using the improved MediaPipe framework the Z value of the joint point is corrected for the human tilt angle through statistics and a better accuracy in the curves could be generated [19]. Various inbuilt attributes were used to detect the landmarks for body parts, such as the nose, wrists, elbows, and shoulders. These landmarks' locations are then employed for additional computations and analysis, like calculating joint angles and counting [20].

3.2. OpenCV

OpenCV provides a real-time optimized Computer Vision library, tools, and hardware. By simply adding z dimension to the prediction in 3D pose estimation, it is possible to convert a 2D image into a 3D image, which aids in the correct prediction of the spatial placement of a depicted item [21].

3.3. Preprocessing

The recorded videos were processed using OpenCV [22] for uploaded videos. Frames from the videos were extracted, and the resolution was standardized to 640x480 pixels to ensure consistent input size for subsequent processing steps. Image enhancement techniques were also applied to improve the quality and reduce frame noise. OpenCV was utilized for the live camera feed to capture and preprocess the video frames in real-time [23]. The frames were resized and enhanced for optimal processing.

MediaPipe and OpenCV were combined to process the chosen video stream. Both submitted films and live camera feeds may be processed without issues due to the integration.

3.4. Landmark Detection

The pose estimation algorithm detected and localized key body landmarks, such as joints and key points, using the trained model. These landmarks were crucial for analyzing the participants' body postures during the exercises. OpenCV was utilized to visualize the estimated poses and landmarks on the frames [24]. The detected landmarks were overlaid onto the frames using OpenCV's drawing functions. This provided real-time visual feedback to the participants, enabling them to observe and adjust their body postures during the exercises. Metrics such as joint angles and distances between specific body parts were calculated based on the detected landmarks [25]. These metrics provided objective measurements for evaluating the correctness and effectiveness of the performed exercises.

If the average joint angle is below the threshold (indicating the start of an exercise), increment the exercise count accordingly. When the angle exceeds the threshold (indicating the completion of an exercise), the current count is displayed, and the auditory feedback is activated. The Raspberry Pi board was configured using a VNC server with the help of the VNC Viewer application. A headless operation through VNC was deployed to access the Raspberry Pi's desktop remotely. Python code files and video datasets were internally stored on a 16 GB SD card. The implementation flow of the system design is shown in Figure 1.

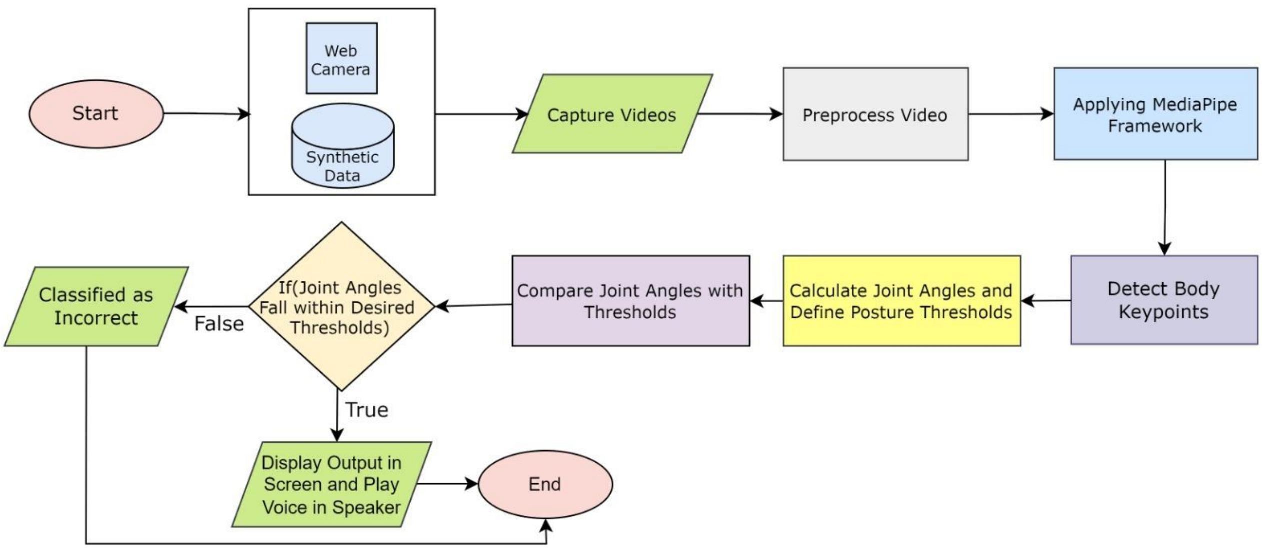


Figure 1. Conceptual working flow implementation of the physiotherapy exercise analysis.

The process starts by using the data already stored in the memory (or) by capturing the user's live video data. The data preprocessing is done to standardize the resolution and reduce noise in the frames. The proposed human pose estimation frameworks are then applied, and the body landmarks are detected. The average joint angles of the input data are calculated and compared with the prescribed angles (threshold levels). If these angles lie within the range, output is presented- the voice output through the speakers and count on the monitor display. If the algorithm cannot detect any landmarks, then the video is considered incorrect. Steps for an automated exercise counting algorithm using OpenCV and Mediapipe for real-time tracking are given in Algorithm 1.

Algorithm 1. Automated exercise counting algorithm using OpenCV and Mediapipe for real-time tracking.

Steps

Input: Video stream or recorded video file containing human poses

Output: Displayed video frames with annotated landmarks and exercise count, Text-to-speech announcements, and corrections

Start

Initialize the video capture to obtain the input video stream or load the recorded video

Create an instance of the pose estimation model using MediaPipe

while frames available in the video **do**

    Read the next frame from the video

    Resize the frame to a standardized size

    Process into pose estimation model and obtain landmarks

    Extract specific landmarks - wrists, shoulders, waist

    Calculate the average joint angle (j)

        if j < threshold value **then**

            exercise_count ← 1

        else if exercise_count ← 1 AND j > threshold value

            exercise_count ← exercise_count + 1

        else

            exercise_count ← 0

    Display video frame with landmarks and update count

    if exercise_count reaches a specific milestone (e.g. 10,20) **then**

        Use text-to-speech to announce the milestone

end while

end

The algorithm is implemented to monitor exercise repetitions and joint angles using MediaPipe's pose estimation model. It starts by initializing the video capture and creating a pose estimation model. The algorithm then iterates through each video frame, resizing it for consistent processing. The pose estimation model extracts landmarks such as wrists, shoulders, and waist. The video frame is displayed with the extracted landmarks and the exercise count is updated accordingly. If the exercise count reaches a specific milestone (e.g., 10, 20), a text-to-speech feature can be used to announce the milestone.

This algorithm provides a framework for real-time exercise monitoring and feedback based on joint angle analysis. It can be customized with specific threshold values and milestones based on the desired exercise goals. By incorporating pose estimation techniques and utilizing MediaPipe, the algorithm offers a robust solution for exercise tracking and performance evaluation. The average joint angle can be calculated using equation (1).

$$y = \frac{\sum_{i=1}^{n} xi}{n}, i = 1, 2. \ldots . n \quad (1)$$

where y= average joint angle calculated; x_i = joint angle in the i^{th} repetition of the exercise; n = number of repetitions of exercise performed by the user

The sum of the angles at a particular joint is calculated and divided by the number of times the exercise is performed, resulting in a quantitative measure of the average joint movement or position observed during the exercise. This is a useful metric to evaluate the consistency and effectiveness of the exercise performance.

While many existing systems use basic angle thresholds to count exercise repetitions, our designed system integrates real-time visual and audio feedback mechanisms, which is a significant improvement. With the help of this, users may adjust their posture in real time and receive quick feedback on how they are performing their exercises. This is very important in physiotherapy settings, where precise motions are essential for successful recovery outcomes. In contrast to the simple counting methods available on many websites, our system uses newly developed and revised body landmark recognition models from MediaPipe and OpenCV. These modifications provide more reliable and precise position estimation, improving the feedback's accuracy and usefulness. Our system counts repetitions and stands out as a useful resource for physiotherapists and patients who need dependable, in-the-moment exercise execution advice because of its comprehensive approach.

3.5. Real-time Feedback Mechanism

This real-time feedback loop is essential for physiotherapy to be effective, where precise motions are required for recovery. OpenCV's drawing functions are employed to overlay important spots and skeleton lines onto video frames to provide visual feedback. When the system determines that the participant's posture is improper, it highlights the exact joints or body regions that require modification. This is accomplished by altering the color of the landmarks or adding extra markers, such as arrows or bounding boxes, around the areas that require rectification. The monitor's real-time display allows participants to see their posture instantly and make any needed modifications. Audio warnings give participants quick audio feedback when their posture deviates from the proper form or when an activity repeat is tallied. The Raspberry Pi board uses a simple Python audio module to create these alarms. This is accomplished using the pygame library, which is well-known for its simple use for playing sound files. Pre-recorded audio messages or tones are broadcast over Raspberry Pi-connected speakers to assist the participant. For example, if the participant's joint angles go outside the allowed range, an alarm may sound, suggesting that they should adjust their posture.

4. Results and Discussion

The total count of the exercise being done during the live video or live camera session is displayed. The joint angles are calculated by considering the positions of relevant body joints in the captured 3D space [26]. For each exercise, joint angles are extracted at relevant time intervals (e.g., at the starting position, during the downward motion, at the lowest point, during the upward motion, and at the ending position). The average joint angle is calculated by summing up the joint angles for each exercise and dividing by the total count. The actual ground truth data was matched with the detected count. Here, in total, five counts are considered. The prescribed average joint angles in five types of spinal exercise are given in Table 2. And, the prescribed average joint angles in five types of cardiovascular exercises are given in Table 3.

Table 2. Prescribed average joint angles in five types of spinal exercise.

Physiotherapy Exercise Name	Prescribed Average Joint Angle (for 5 counts)
Cat-cow Stretch	▪ Spine flexion: 38.5° ▪ Spine extension: 27.8° ▪ Knee flexion: 5.6° ▪ Shoulder protraction: 14.9° ▪ Shoulder retraction: 14.8°
Partial Curl	▪ Spine flexion: 32.9° ▪ Hip extension: 16.86°
Bird dog	▪ Spine extension: 10.6° ▪ Hip extension: 16.88° ▪ Shoulder flexion: 20° ▪ Knee flexion: 11.2°

Squats	▪ Ankle dorsiflexion: 31° ▪ Hip flexion: 81° ▪ Spine extension: 2.2° ▪ Knee flexion: 90°
Back extension	▪ Facet joint: 2.2° ▪ Sacroiliac joint: 0.6° ▪ Hip joint: 83.5° ▪ Shoulder joint: 1.7°

Table 3. Prescribed average joint angles in five types of cardiovascular exercises.

Physiotherapy Exercise Name	Prescribed Average Joint Angle (for 5 counts)
Push Ups	▪ Shoulder protraction: 11.5° ▪ Shoulder retraction: 15.5° ▪ Elbow flexion: 118.7° ▪ Elbow extension: 1.7° ▪ Spine: 0°(neutral position)
Bridge	▪ Ankle dorsiflexion: 12.2° ▪ Ankle plantar-flexion: 5.4° ▪ Knee flexion: 89° ▪ Knee extension: 1.7° ▪ Spinal extension: 22.4° ▪ Hip flexion: 41° ▪ Hip extension: 0.8°
Shoulder Rolls	▪ Shoulder abduction: 33.5° ▪ Shoulder internal rotation: 25.9° ▪ Shoulder external rotation: 26°

By calculating the average joint angles, insights are gained into the form, technique, and alignment of the body, and the correctness of a pose is evaluated. When joint angles deviate from the prescribed range, it may be a sign of incorrect form or compensatory movements, which might lead to injuries or lessen the efficiency of the exercise. This method accurately tracked key body landmarks in varying lighting conditions or during complex body poses. Certainly, there is a limitation when an occlusion occurs during an exercise. Real-time feedback and guidance are provided to users, facilitating proper form and technique. The back extension exercise is shown in Figure 2.

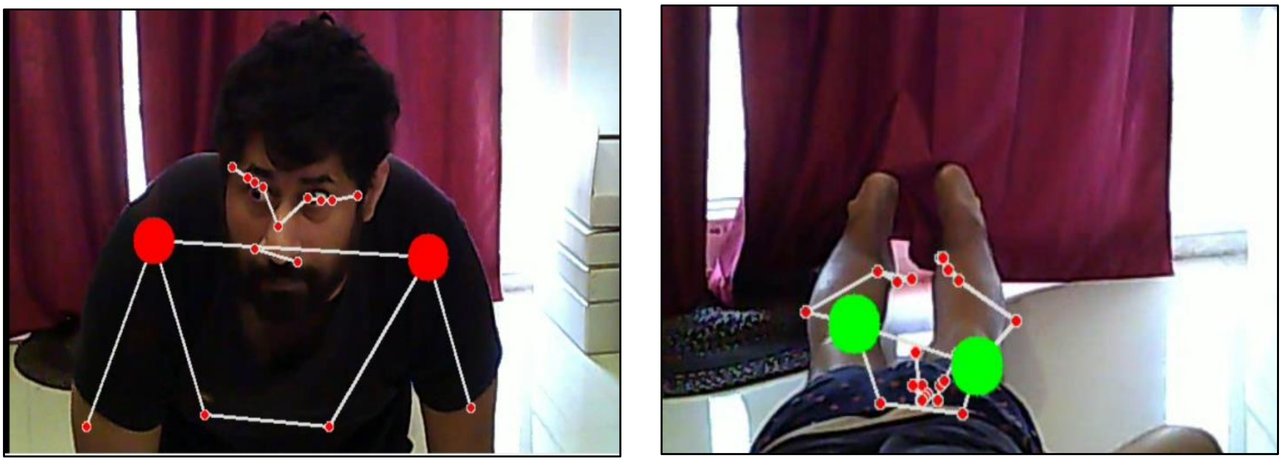


Figure 2. Back extension exercise being performed.

All the exercises and their respective joint angles are shown in the following figures in the form of graphs. The exercises related to the spine are shown in Figures 3 to 7. All the joint angles involved while performing the Cat-cow stretch exercise are shown in Figure 3. The parts involved in this exercise are the spine, shoulder, and knee. This figure shows the subplots for five iterations of the exercise. All angles in these subplots are in degrees.

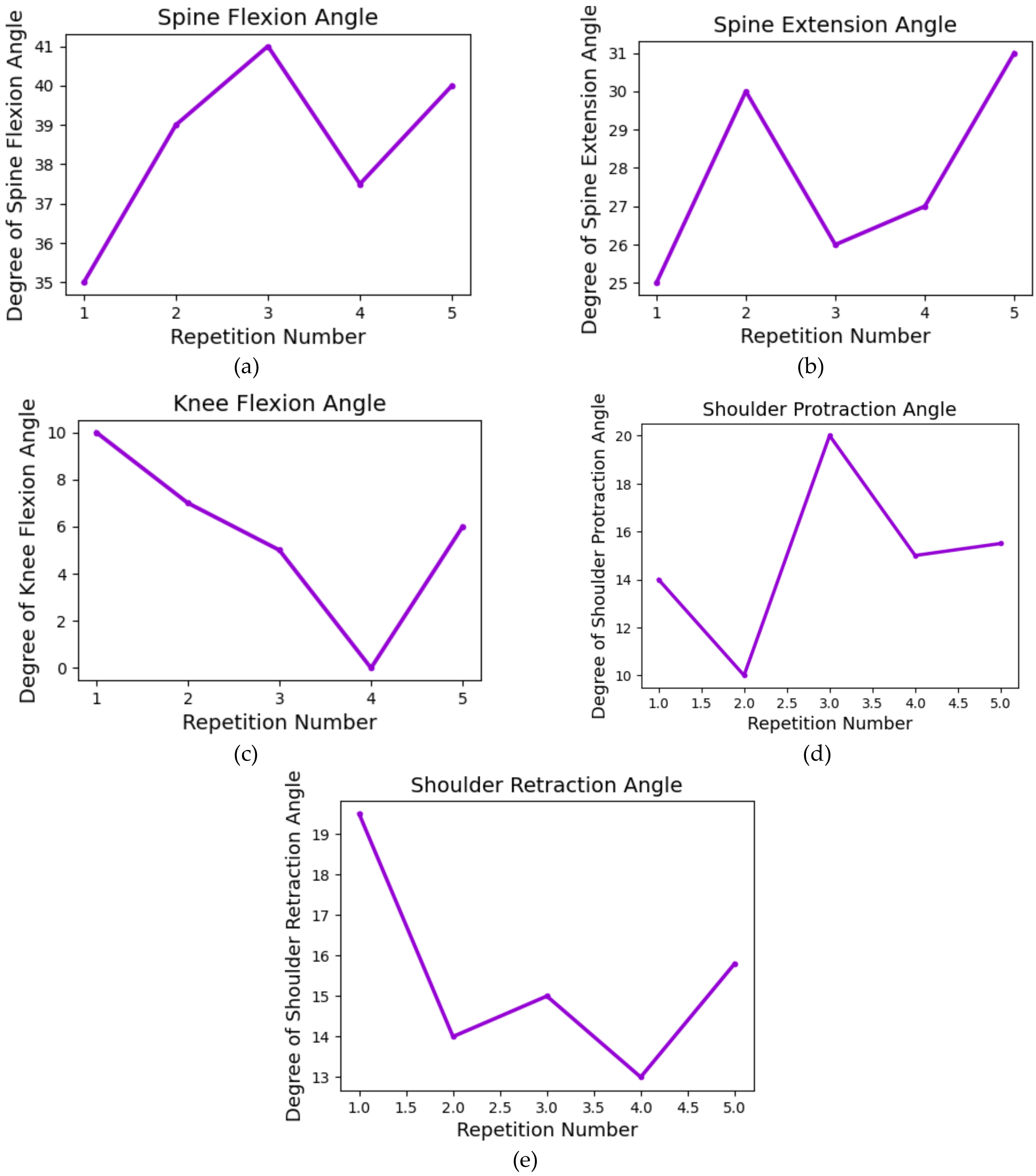
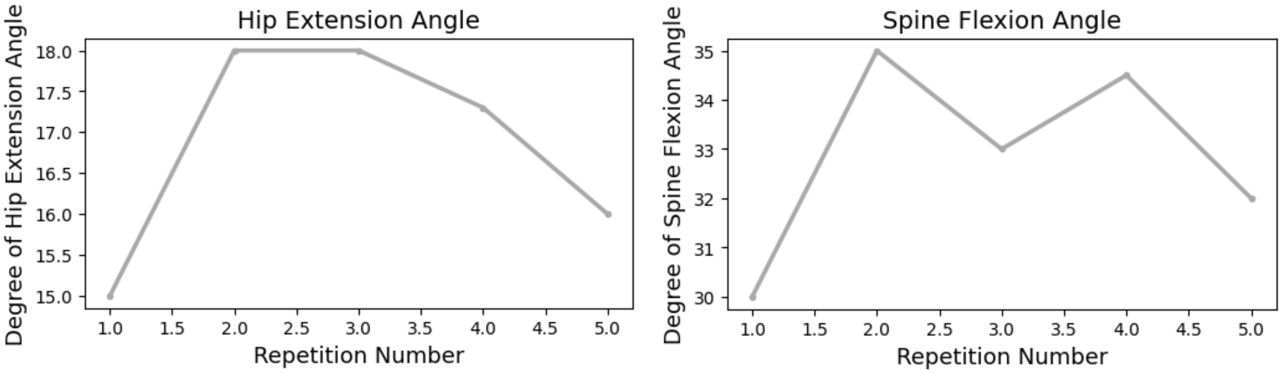


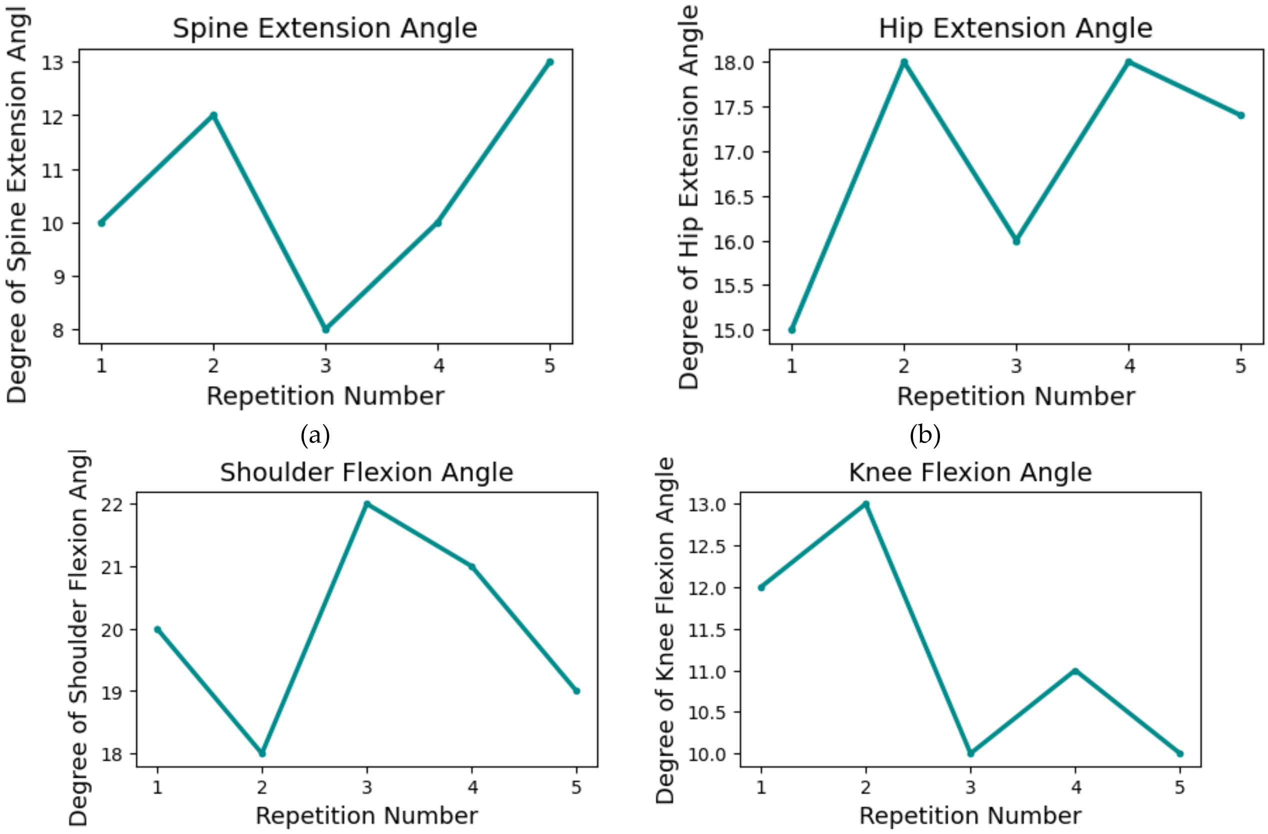
Figure 3. Different kinds of angles are involved in the cat-cow stretch exercise.

All the joint angles involved in the partial curl exercise are shown in Figure 4. The parts involved are the hip and spine. This figure shows the subplots for five iterations of the exercise. All angles in the subplots are in degrees. All the joint angles involved in the bird-dog exercise are shown in Figure 5. The parts involved are the spine, knee, and shoulder. This figure shows the subplots for five iterations of the exercise. All angles in the subplots are in degrees.



(a) (b)

Figure 4. Different kinds of angles involved in the partial curl stretch exercise.



(c) (d)

Figure 5. Different kinds of angles are involved in bird dog exercise.

The angles related to the cardiovascular exercises are shown in Figures 6 and 7. All the joint angles involved in the push-up exercise are shown in Figure 6. The parts involved are the shoulder and elbow. This figure shows the subplots for five iterations of the exercise. All angles in the subplots are in degrees. All the joint angles involved in the bridge exercise are shown in Figure 7. The parts involved are the knee, ankle, spine, and hip. This figure shows the subplots for five iterations of the exercise. All angles in the subplots are in degrees.

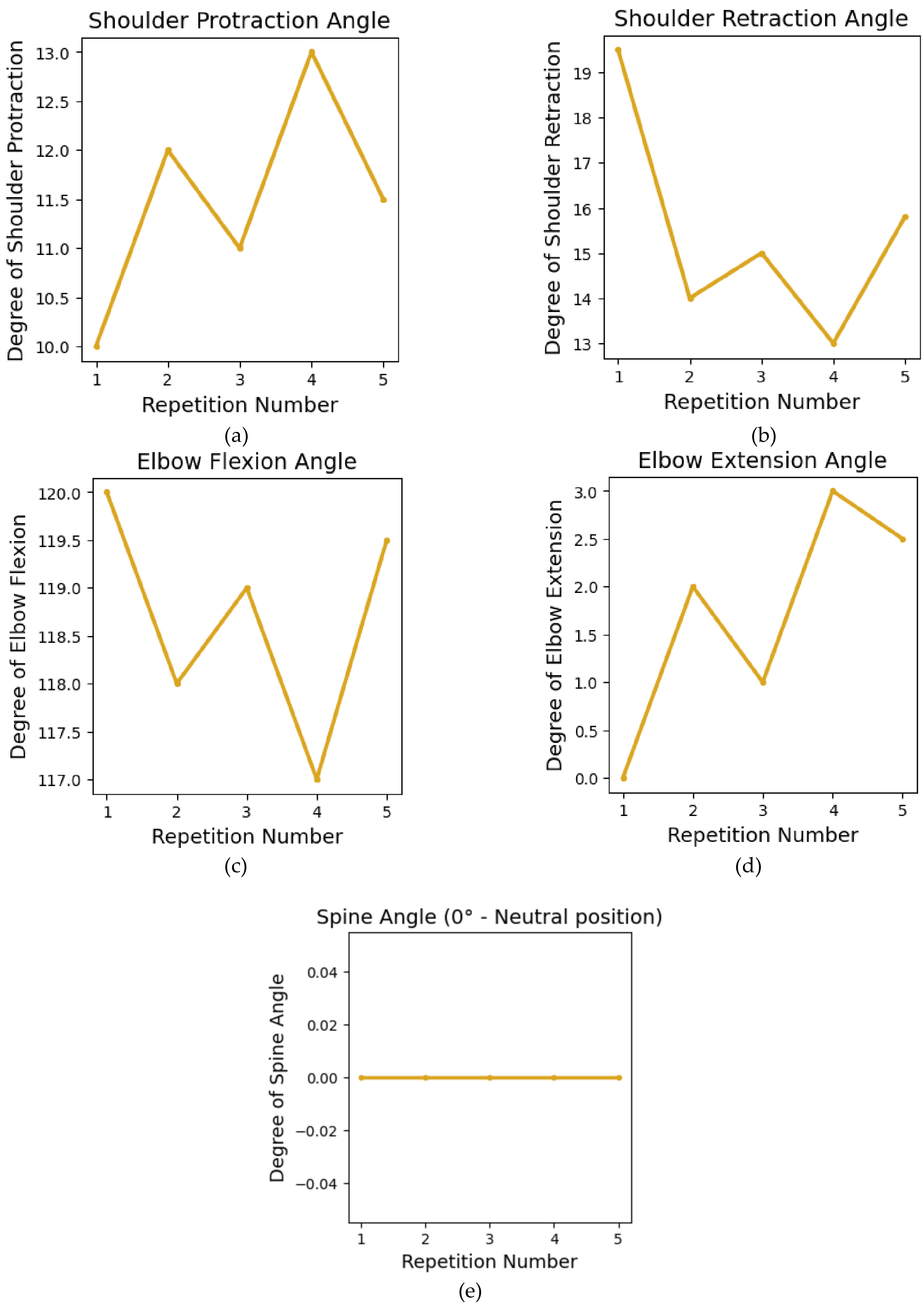


Figure 6. Different kinds of angles are involved in push-up exercises.

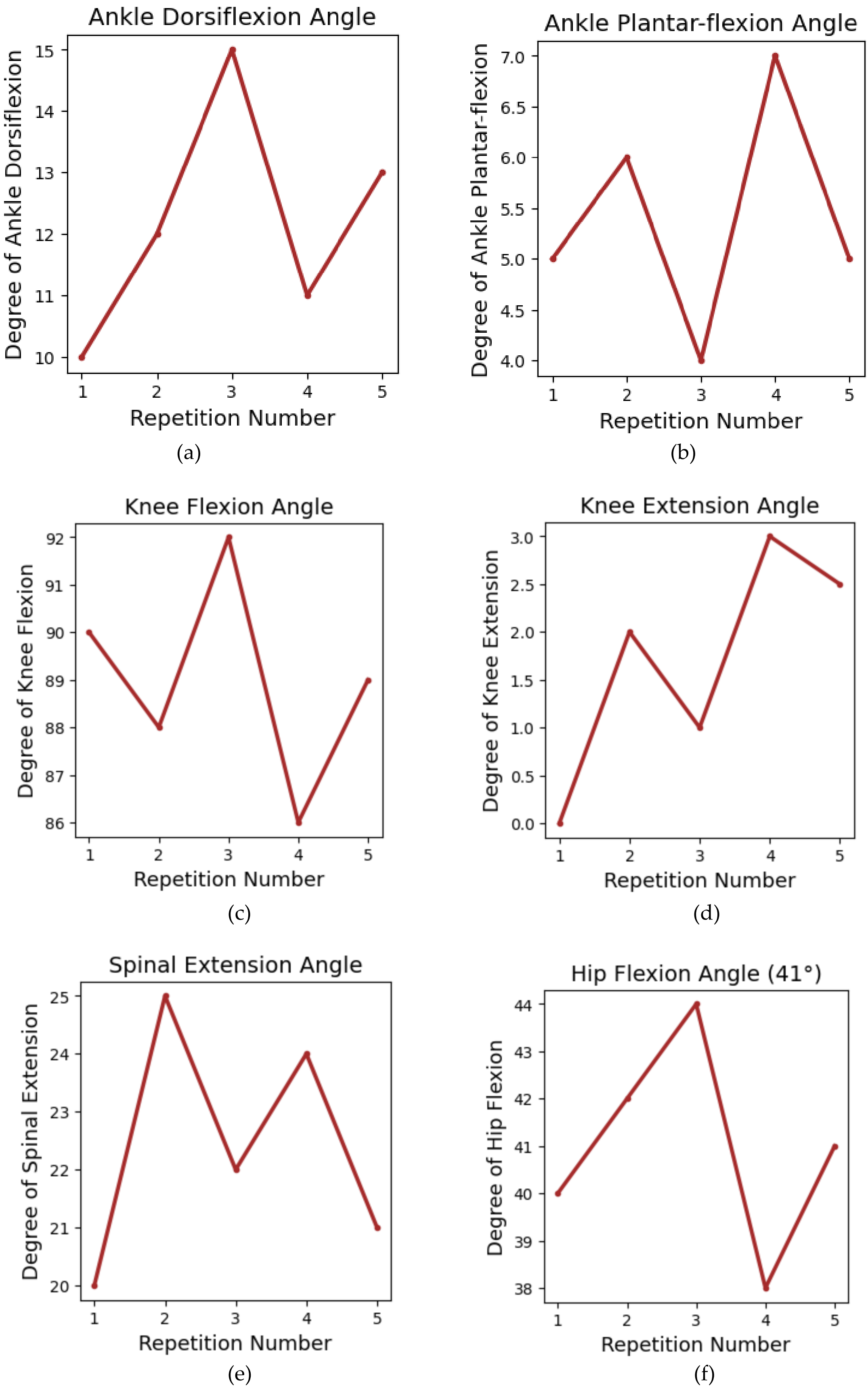


Figure 7. Different kinds of angles are involved in bridge exercise.

In addition to tracking exercise repetitions, our system offers instant feedback on how well each action is performed. Joint angles are calculated and compared to predetermined criteria to do this. For instance, the system determines the angle at which the torso and upper arm form during a shoulder raise exercise. The device instantly gives the user visual and audio feedback if the angle goes outside of the advised range, assisting them in correcting their form.

The comparison between OpenPose and OpenCV is given in Table 4. This table shows how an OpenCV framework is superior to the OpenPose framework regarding flexibility, integration, and performance. The obtained accuracy while the users performed spinal exercises is shown in Figure 8. From this figure, the accuracy obtained for the back extension physiotherapy exercise is the maximum compared to other spinal exercises. The accuracy obtained is 93.2% for back extension, 85.6% for squats, 85% for a bird dog, 90% for partial curl, and 89.5% for cat-cow stretch exercises, respectively.

Table 4. Comparison between OpenPose and OpenCV.

OpenPose	OpenCV
▪ OpenPose is built on deep learning models. It employs intricate neural network topologies, like multi-stage convolutional networks, to find and localize human key points.	▪ OpenCV is a comprehensive computer vision library that provides a wide range of pre-built functions and algorithms for various tasks, including pose estimation. In comparison to OpenPose, it provides a simpler and more user-friendly API.
▪ It may require additional effort and expertise to adapt it to specific use cases.	▪ With its diverse set of functions and algorithms, it offers more flexibility and easier integration.
▪ Computationally intensive, it requires substantial processing power, memory, and high-end GPU.	▪ Less resource-intensive compared to the deep learning models used in OpenPose, often optimized for efficient execution on various hardware platforms.
▪ Limited flexibility and customization. The customization of the network architecture might be challenging.	▪ OpenCV and Mediapipe provide flexibility in terms of customization, adjusting parameters, and adding more computer vision algorithms if necessary.

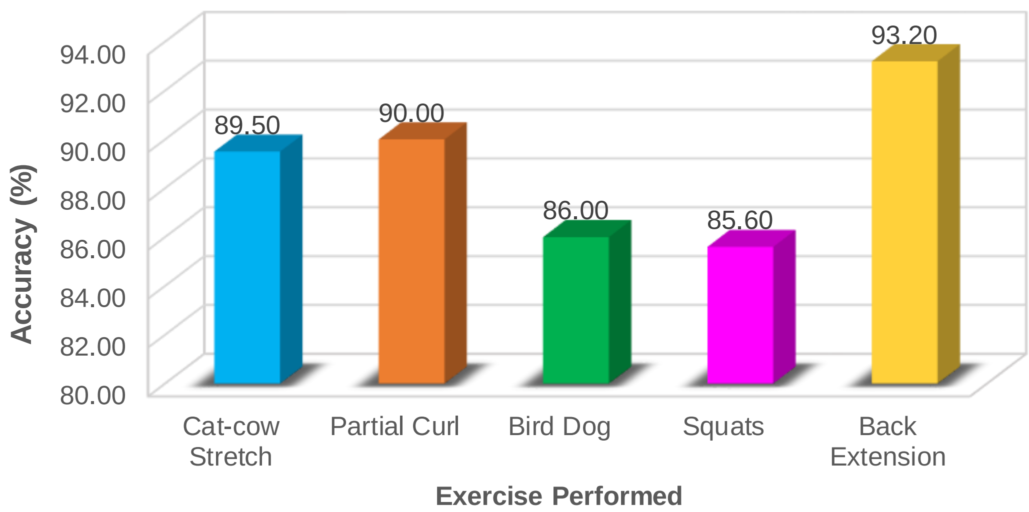


Figure 8. Obtained accuracy while the users performed spinal exercises.

The obtained accuracy while the users performed cardiovascular exercises is shown in Figure 9. This figure shows that the accuracy obtained for the push-up physiotherapy exercise is the maximum when compared to other cardiovascular exercises. The accuracy obtained is 96.5% for push-ups, 88% for bridge, and 85.98% for shoulder roll exercises, respectively.

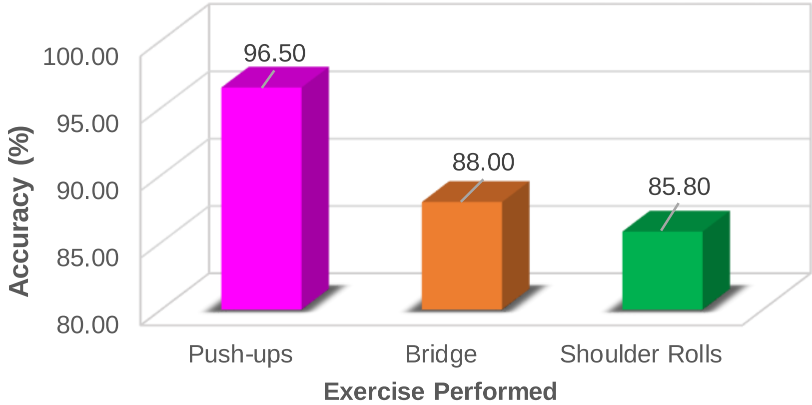


Figure 9. Obtained accuracy while the users performed cardiovascular exercises.

5. Conclusions

In this study, a system was developed to estimate human postures utilizing OpenCV and MediaPipe. The system's tracking and detection capabilities were thoroughly evaluated to assess its accuracy in accurately identifying human stances. The successful monitoring of important human body landmarks achieved real-time, highly accurate human pose estimation. OpenCV and MediaPipe offered several advantages over. The system showed superior accuracy and robustness, making it a favorable choice for physiotherapy-related tasks. Also, the voice acknowledgment makes the system more user-friendly. Additionally, the user's ability to choose between live camera feeds and video uploads increased the usefulness and scenario adaptability of the system. This system can also be used for fitness monitoring, rehabilitation exercises, and sports performance analysis. We can also incorporate a gesture recognition system here.

5.1. Ethical Considerations

The research was conducted following ethical standards, which guaranteed participant informed permission and upheld the privacy and confidentiality of their data. The study was carried out under all applicable laws and ethical guidelines.

5.2. Limitations

The project focuses on a specific set of physiotherapy exercises. However, numerous other exercises and movement patterns could benefit rehabilitation or fitness. The scope of the project may not cover all possible exercises. Moreover, although the UI-PRMD dataset provided a solid foundation, its generalizability to all physiotherapy exercises and patient demographics may be limited. Environmental factors such as lighting conditions, background clutter, and camera angles may affect the system's accuracy. Adverse conditions or distractions in the surroundings could impact the accuracy of joint angle calculations and exercise detection. Future iterations should address these limitations by integrating adaptive algorithms and enhancing dataset diversity to improve overall effectiveness in clinical and home-based physiotherapy settings.

5.3. Future Scope

This work can be extended further using the newly developed frameworks like AlphaPose and EfficientPose. The purpose of the AlphaPose [27, 28] framework is to provide precise joint localization and detailed pose information. It employs deep learning models and advanced algorithms to achieve highly accurate pose estimation results. Also, it can handle challenging pose estimation scenarios, including occlusions and complex poses. EfficientPose [29, 30] is a pose estimation framework known for its efficient and lightweight architecture. It is developed to offer a decent balance between speed and precision. For applications where real-time performance and minimal computational demands are essential, the EfficientPose framework is more suitable.

Author Contributions: Conceptualization, K.V.D. and R.S.; methodology, M.M.V.C. and Y.V.P.K.; software, K.P.P. and D.G.; validation, C.P.R. and M.S.; formal analysis, K.V.D.; investigation, M.M.V.C.; resources, C.P.R.; data curation, Y.V.P.K.; writing—original draft preparation, K.P.P.; writing—review and editing, D.G.; visualization, M.S.; supervision, C.P.R.; project administration, R.S.. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

[1] Kertesz, C. Physiotherapy Exercises Recognition Based on RGB-D Human Skeleton Models. *2013 European Modelling Symposium, Manchester, United Kingdom* **2013**, 21–29. https://doi.org/10.1109/EMS.2013.4

[2] Herbert, R. D.; Maher, C. G.; Moseley, A. M.; Sherrington, C. Regular review: Effective physiotherapy. *British Medical Journal* **2001**, *323*(7316), 788–790. https://doi.org/10.1136/bmj.323.7316.788

[3] Rucha, G. (2023, September 9). India. *Physiopedia*. https://www.physio-pedia.com/India

[4] Piñero-Fuentes, E.; Canas-Moreno, S.; Rios-Navarro, A.; Domínguez-Morales, M.; Sevillano, J. L.; Linares-Barranco, A. A Deep-Learning Based Posture Detection System for Preventing Telework-Related Musculoskeletal Disorders. *Sensors* **2021**, *21*(15), 5236. https://doi.org/10.3390/s21155236

[5] Khan, Rushina., Deogiri Inst of Engg. Management Studies. Telecommunting: The Problems Challenges During Covid-19. *International Journal of Engineering Research and Technology* **2020**, *V9*(07), IJERTV9IS070432. https://doi.org/10.17577/IJERTV9IS070432

[6] Nag, P. K. Musculoskeletal Disorders: Office Menace. In P. K. Nag, *Office Buildings*. 105–126. Springer Singapore **2019**. https://doi.org/10.1007/978-981-13-2577-9_4

[7] Yamao, K.; Kubota, R. Development of Human Pose Recognition System by Using Raspberry Pi and PoseNet Model. *2021 20th International Symposium on Communications and Information Technologies (ISCIT), Tottori, Japan* **2021**, 41–44. https://doi.org/10.1109/ISCIT52804.2021.9590593

[8] Kulkarni, K. M.; Shenoy, S. *Table Tennis Stroke Recognition Using Two-Dimensional Human Pose Estimation* **2021**. https://doi.org/10.48550/ARXIV.2104.09907

[9] Zhang, Y.; You, S.; Karaoglu, S.; Gevers, T. Multi-person 3D pose estimation from a single image captured by a fisheye camera. *Computer Vision and Image Understanding* **2022**, 222, 103505. https://doi.org/10.1016/j.cviu.2022.103505

[10] Yeo, N. Posture detection for physical therapy application. Final Year Project (FYP), *Nanyang Technological University, Singapore* **2023**. https://hdl.handle.net/10356/166826

[11] Nishchal, K. A.; Prajwal, R. V.; Prakruthi, B. M.; Venika, S.; Anil, K. C. Vision Based Human Fall Detection System. *International Research Journal of Modernization in Engineering Technology and Science* **2023**. https://doi.org/10.56726/IRJMETS37625

[12] Kontadakis, G.; Chasiouras, D.; Proimaki, D.; Halkiadakis, M.; Fyntikaki, M.; Mania, K. Gamified platform for rehabilitation after total knee replacement surgery employing low cost and portable inertial measurement sensor node. *Multimedia Tools and Applications* **2020**. *79*(5–6), 3161–3188. https://doi.org/10.1007/s11042-018-6572-6

[13] Thar, M. C.; Winn, K. Z. N.; Funabiki, N. A Proposal of Yoga Pose Assessment Method Using Pose Detection for Self-Learning. *2019 International Conference on Advanced Information Technologies (ICAIT)* **2019**, 137–142. https://doi.org/10.1109/AITC.2019.8920892

[14] Rathour, N.; Khanam, Z.; Gehlot, A.; Singh, R.; Rashid, M.; AlGhamdi, A. S.; Alshamrani, S. S. Real-Time Facial Emotion Recognition Framework for Employees of Organizations Using Raspberry-Pi. *Applied Sciences* **2021**, *11*(22), 10540. https://doi.org/10.3390/app112210540

[15] Ryberg, S.; Jansson, J. *Real-time object detection robot control : Investigating the use of real time object detection on a Raspberry Pi for robot control (Dissertation).* Retrieved from https://urn.kb.se/resolve?urn=urn:nbn:se:kth:diva-320969. **2022**.

[16] Chen, P.-J.; Hu, T.-H.; Wang, M.-S. Raspberry Pi-Based Sleep Posture Recognition System Using AIoT Technique. *Healthcare* **2022**, *10*(3), 513. https://doi.org/10.3390/healthcare10030513

[17] Yalin, L.; Aleksandar, V.; Min, X. A Deep Learning Framework for Assessing Physical Rehabilitation Exercises. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **2020**, *28*(2), 468-477. https://doi.org/10.1109/TNSRE.2020.2966249

[18] Lugaresi, C.; Tang, J.; Nash, H.; McClanahan, C.; Uboweja, E.; Hays, M.; Zhang, F.; Chang, C.-L.; Yong, M. G.; Lee, J.; Chang, W.-T.; Hua, W.; Georg, M.; Grundmann, M. MediaPipe: A Framework for Building Perception Pipelines (arXiv:1906.08172). arXiv. **2019.** http://arxiv.org/abs/1906.08172

[19] Lin, Y.; Jiao, X.; Zhao, L. Detection of 3D Human Posture Based on Improved Mediapipe. *Journal of Computer and Communications*, **2023**, *11*(02), 102–121. https://doi.org/10.4236/jcc.2023.112008

[20] On-device machine learning for everyone *MediaPipe*. **2023**. https://developers.google.com/mediapipe

[21] Podduturi, H. V. R.; Varla, C.; Gopaldinne, K. R.; Bhukya, N.; Reddy Nallagondu, R. K.; Bapiraju, G. S. Smart Trainer using OpenCV. *2023 International Conference on Innovative Data Communication Technologies and Application (ICIDCA), Uttarakhand, India* **2023**, 477–480. https://doi.org/10.1109/ICIDCA56705.2023.10099780

[22] Mahato, A. (2023, September 9). Getting started with Image Processing Using OpenCV. Retrieved from Analytics Vidhya website: https://www.analyticsvidhya.com/blog/2023/03/getting-started-with-image-processing-using-opencv/

[23] Naveenkumar, M.; Vadivel, A. OpenCV for Computer Vision Applications [Conference session]. Conference: *Proceedings of National Conference on Big Data and Cloud Computing (NCBDC'15), Trichy, India* **2015**. https://www.researchgate.net/publication/301590571_OpenCV_for_Computer_Vision_Applications#fullTextFileContent

[24] Xiangxin, Zhu.; Ramanan, D. Face detection, pose estimation, and landmark localization in the wild. *2012 IEEE Conference on Computer Vision and Pattern Recognition* **2012**, 2879–2886. https://doi.org/10.1109/CVPR.2012.6248014

[25] Sunil, D. K.; Nipun, K.; Kumbhkarn, Sumit, K.; Atharva, K.; Shreyash, K. Posture Detection and Comparison of Different Physical Exercises Based on Deep Learning Using Media Pipe, Opencv. *International Journal of Scientific Research in Engineering and Management (IJSREM)* **2023**. https://ijsrem.com/download/posture-detection-and-comparison-of-different-physical-exercises-based-on-deep-learning-using-media-pipe-opencv/

[26] Alwani, A. A.; Chahir, Y.; Goumidi, D. E.; Molina, M.; Jouen, F. 3D-Posture Recognition Using Joint Angle Representation. In A. Laurent, O. Strauss, B. Bouchon-Meunier, R. R. Yager (Eds.), *Information Processing and Management of Uncertainty in Knowledge-Based Systems* **2014**, *443*, 106–115. Springer International Publishing. https://doi.org/10.1007/978-3-319-08855-6_12

[27] Fang, H.-S.; Li, J.; Tang, H.; Xu, C.; Zhu, H.; Xiu, Y.; Li, Y.-L.; Lu, C. AlphaPose: Whole-Body Regional Multi-Person Pose Estimation and Tracking in Real-Time. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **2023**, *45*(6), 7157–7173. https://doi.org/10.1109/TPAMI.2022.3222784

[28] Machine Vision and Intelligence Group @ SJTU. (2023, September 9). Real-Time and Accurate Full-Body Multi-Person Pose Estimation and Tracking System. Retrieved from https://github.com/MVIG-SJTU/AlphaPose

[29] Bukschat, Y.; Vetter, M. EfficientPose: An efficient, accurate and scalable end-to-end 6D multi object pose estimation approach (arXiv:2011.04307). arXiv. **2020**. http://arxiv.org/abs/2011.04307

[30] Ybkscht. (2023, September 9). EfficientPose. Retrieved from https://github.com/ybkscht/EfficientPose