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Implementation of Geriatric Agility Detection Using MediaPipe Pose

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***Abstract*: It is crucial to identify frailty in the elderly population early and accurately to prevent falls and muscle movement loss This makes early intervention possible as determined appropriate by the medical professionals and prolongs muscular activity. Following the Covid-19 outbreak, an enormous. The ageing population has been restricted to their dwellings, which has significantly impacted their physical health extent. The elderly is more vulnerable to these impacts mostly as a result of lengthy lockdowns and travel restrictions also a decline in social support. The research aims to develop a technique to aid older people in determining their level of frailty Geriatric Agility Detection with Early and Accurate 30 second chair-stand test. Medical care is described as geriatric. Agility, a term used to describe the ability to move quickly and freely is directly related to the reduction of falls among older people.**

***Keywords*: Geriatric, Agility, Frailty, Reduction of falls, 30 second chair stand test.**

1. Introduction

According to WHO, the number and proportion of people aged 60 years and older will increase to 1.4 billion by 2030 and 2.1 billion by 2050 [1]. Therefore, proper diagnosis and rehabilitation programs need to be designed to prevent immobility and postural instability, decreasing the risk of falls and downstream decline on a frequent and consistent basis. With the ongoing pandemic, the likelihood of age-related cognitive and functional problems have increased significantly due to decrease in physical activity and lack of accessing services [2]. Thus, we introduce an economical and easy to use method to help the older and frail population self-assess and deal with such problems without the requirement of a healthcare provider.

The method revolved around the results obtained after performing the 30 second chair stand test [3] to help determine the level of agility of a user according to their age and gender. This test is part of the Senior Fitness Test Protocol [4], and is designed to test the functional fitness of seniors. The user sits in the middle of the seat, with their feet shoulder width apart, flat on the floor. The arms are to be crossed at the wrists and held close to the chest. From the sitting position, the subject stands completely up, then completely back down, and this is repeated for 30 seconds. We count the total number of complete chair stands (up and down equals one stand).

We propose using media-pipe's blaze pose machine learning model for this application, which can run on a small number of processing-powered machines. Human posture estimation has improved significantly as a result of the rapid development of deep convolutional neural networks, which helps to accurately assess the exercise the user is doing. Human pose estimation locates body vital points in order to accurately distinguish people's postures in photos or videos. This is a necessary step before beginning the workout analysis. We offer a method for aiding in the resolution of this challenge by sensing a user's body position throughout a workout and comparing it to a computed angle between limbs while keeping a good form for the above said exercise. We represent the human body as a collection of limbs and calculate angles between them to detect incorrect posture and give accuracy to the user, based on the current breakthrough in deep learning for human body posture estimation. Other elements of the blazpose model [5] include repetition counting and real-time body movement identification.

The objective of our study was to apply the current strategy to detect frailty and make it accessible to the larger population of old people. The approach is hassle free, self-accessible and allows a user make comparative study without the need of a technician making them more independent. The software can be used on a laptop or camera and can be viewed as a form of cumulative solution to achieve better physique and reduce potential risks of injury.

2. Background of the Work

All traditional approaches involve the use of expensive hardware to capture and evaluate the results of the 30 Chair Stand Test. These hardware components do provide a deep understanding of the results obtained when the geriatric test is performed by various participants. But their major drawback is that it makes these tests difficult to perform without technical assistance and in a clinical environment. Below is the flow-diagram explaining the traditional Geriatric-agility 30 second chair stand test (30 CST) detection using hardware components.

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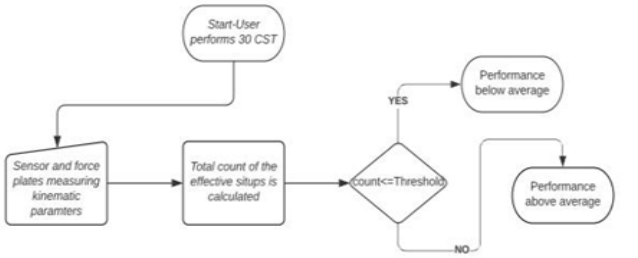

Fig. 1. Flow diagram of traditional geriatric test using pressure plates and sensors

Later, the concept of human detection using Artificial Intelligence and Machine Learning came into existence. Human pose estimation is the process of inferring poses from photographs or videos, and it may be done in both 2D and 3D. We found a number of techniques for recognizing poses from previous years. We looked at a number of studies from 2017 and noticed that the topic of machine learning is attracting an increasing amount of interest from academic's communities. Many of the researchers advocated that the new system work in conjunction with previous technologies to provide the state-of-the-art results. Deep convolutional neural networks are now the most popular solutions. There are two common approaches: Regression the placement of key-points and the estimation of key-point heat maps, then selecting the sites with the highest heat values as candidates for the main points.

The paper produced by Nora Millor and others discusses the relevance of the 30-s Chair Stand Test as an important parameter to discriminate among healthy, prefrail and frail populations using sensors such as accelerometers and gyroscopes [6].

In the year 2019, Xie et al introduced Open Pose, a human pose estimation method. However, its efficiency is really low. To solve this, deep learning algorithms for recognizing human body positions based on TensorFlow came into picture [7].

3. Methodology

Pose estimation is a machine learning challenge that guesses the geographical locations of various body components to estimate a person's pose from an image or video (key points). Pose estimation is a computer vision technique for tracking a person's or an object's movements. This is normally accomplished by locating critical spots for the things in question. We may compare different actions and postures and draw conclusions based on these essential points. Later in this section, we will be discussing how media-pipe works in the background and how we exploited its power to boost our application design.

Deep learning has been shown to outperform traditional computer vision approaches in a variety of tasks, including image segmentation and object detection, thanks to the rapid growth of deep learning solutions in recent years. As a result, deep learning techniques have resulted in considerable advancements and improvements in posture estimation jobs. Openpose [8], movenet, deeppose, posnet, bodynet [9], and more deep learning estimation techniques are available. In our instance, we're utilizing a Blazepose since it's Google's most recent model, and it works well on lightweight devices like a browser or a mobile device. As a result, BlazePose can be used to estimate a single pose or a set of poses.

Below diagram shows the methodology we adopted to accurately determine the number of sit-up counts while performing 30 CST.

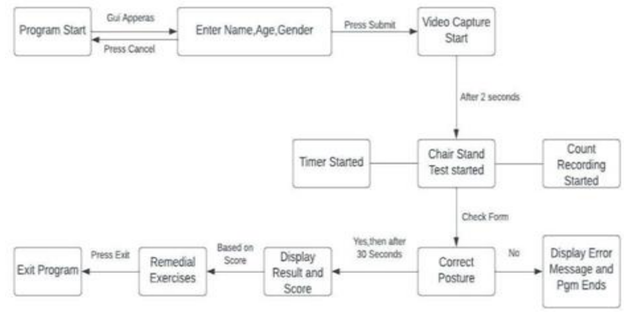

Fig. 2. Flow diagram of geriatric agility test using computer vision

What is BlazePose?

Blaze pose is a real-time posture identification approach for detecting human poses in images and videos. It only works in one mode (single human pose detection). In simple terms, the flame posture is a deep learning model that estimates human pose by identifying body parts such as elbows, hips, wrists, knees, and ankles, and then combining these points to construct a skeletal structure of your pose.

It's a simple model that uses depth-wise separable convolution to deepen the network while lowering parameters, increasing accuracy, and lowering computing costs. From the nose to the left foot index, the Blaze position provides us with a total of 33 essential points that we can exploit as shown in the below diagram [10].

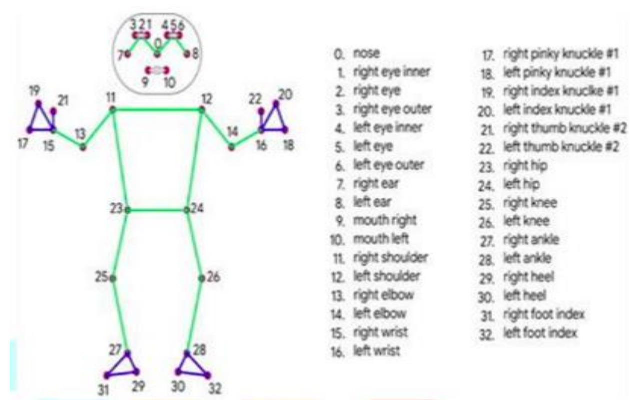

Fig. 3. 33 pose landmarks

Working of BlazePose:

Detector and Estimator are two machine learning models used by Blaze pose. The detector is used to extract the human portion of an image. The images supplied by the detector are fed into an estimator, which produces output.

Human body Modelling:

The placement of human body parts is utilized to generate a human body representation (such as a body skeleton posture) from visual input data in human pose estimation. As a result, human body modelling is an important part in estimating human position. It's used to represent extracted characteristics and key points from visual input data. To define and infer human body postures and generate 2D or 3D poses, a model-based technique is typically utilized. We employ an N-joints stiff kinematic model in which a human body is represented as an entity with joints and limbs that contains body kinematic structure and shape information.

The skeleton-based model, also known as the kinematic model, is used for both 2D and 3D pose estimation. To reflect the human body structure, this adaptable and intuitive human body model comprises a variety of joint configurations and limb orientations. To record the relationships between different body sections, skeleton pose estimation models are used. However, as demonstrated in figure, kinematic models have limitations when it comes to capturing texture or shape information.

4. System and Algorithm Design

We create a user guide application that uses the cv2 module [11] to capture and detect body poses in order to run the programme. The MediaPipe framework and Python programming language are being used to create an application user guide.

There have been numerous exciting research accomplishments using OpenCV as a module for articulating human body tracking, position, and even recognition systems. We capture a real-time image with the laptop's camera, which has a resolution of 640x240 pixels, to process using the MediaPipe framework. Objects for video capture and video writer are constructed. We get the video metadata that will be utilized to make the video capture object. MediaPipe will read the image from OpenCV, do body detection, and create body landmarks, which will return 3D body key points and joints, resembling a skeleton. 3D key points in the body that have been marked in the image will be computed and initialized as a tool for reading pose body and recognition based on body pose that has been initialized before. Below flowchart shows how we have developed an effective algorithm that suits our needs to its best.

Pose detection algorithm:

Input- Picture frames captured from the default camera of the device

Output- Sit Up count, performance feedback and exercise to improve agility.

Step 1: The frames from the camera are converted to RGB format as Python captures the frame in BGR format. RGB format is required for pre-processing of the images.

Step 2: Getting Key points - We choose the default values for detecting pose landmarks and set the ENABLE SEGMENTATION flag to true in the Pose (adjustable)’s API as we want the utility to generate a segmentation landmark and default values do a good job.

The following are some of the MediaPipe pose solution's configurable APIs.

STATIC_IMAGE_MODE: It’s a boolean. If set to True, person detection runs for every input image. This is not necessary for videos, where detection runs once followed by landmark tracking. The default value is False.

MODEL_COMPLEXITY: Default value is 1. It can be 0, 1, or 2. If higher complexity is chosen, the inference time increases.

ENABLE_SEGMENTATION: If set to True, the solution generates a segmentation mask along with the pose landmarks. The default value is False.

MIN_DETECTION_CONFIDENCE: Ranges from [0.0 – 1.0]. As the name suggests, it is the least confidence value for the detection to be considered valid. The default value is 0.5.

MIN_TRACKING_CONFIDENCE: Ranges from [0.0 – 1.0]. It is the minimum confidence value for a landmark to be considered tracked. The default value is 0.5.

Step 3: Calculation of Body Pose angles - We use the shoulder-elbow-wrist and shoulder-hip-knee body points marked by MediaPipe to first calculate the offset distance and then inclination to check for the right form during the exercise.

Offset is calculated using the distance formula:

$$distance = \sqrt{(x2 - x1)^2 + (y2 - y1)^2}$$

where x and y are x-coordinate and y-coordinate of the given body landmark.

We use the vector approach to find the inner angle of three points. The angle between two vectors P_12 and P_13 is given by:

0= arctan(P1P2/P1P3)

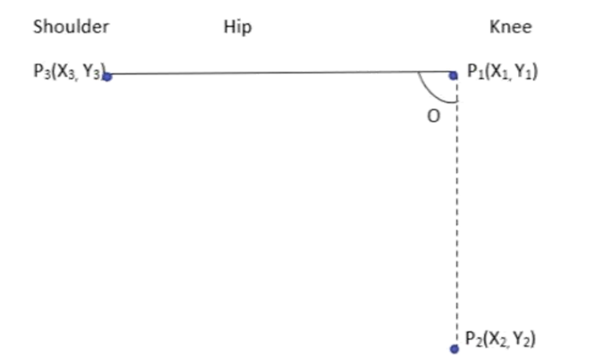

Fig. 5. Vector approach to calculate angle

The angle formed by the shoulder, elbow, and wrist lines in relation to the y-axis is used. The important location in this case is the elbow. The hip line, likewise, connects the knee and the shoulder, with the hip serving as a crucial point.

Step 4 - Conditionals to check for correct body form - On the basis of the posture, whether good or bad, sit up count is calculated and results are displayed. We compare the angle we calculated in Step 2 and compare it with threshold angles we calculated based on different researches.

We know knee height is approx. 49.6 cm in both the genders and 30-CST is administered using a folding chair without armrest, with seat height of 17 inches (43.2 cm) [12]. We use these two heights to determine the best predictor angle using the formula,

O = arccos(AC.AB)/(|AC||AB|)

O is the Approx Threshold Angle which is 110 degrees.

Table 1
Male test subjects

Age	Below average	Average	Above average
60-64	< 14	14 to 19	> 19
65-69	< 12	12 to 18	> 18
70-74	< 12	12 to 17	> 17
75-79	< 11	11 to 17	> 17
80-84	< 10	10 to 15	> 15
85-89	< 8	8 to 14	> 14
90-94	< 7	7 to 12	> 12

Table 2
Female test subjects

Age	Below average	Average	Above average
60-64	< 12	12 to 17	> 17
65-69	< 11	11 to 16	> 16
70-74	< 10	10 to 15	> 15
75-79	< 10	10 to 15	> 15
80-84	< 9	9 to 14	> 14
85-89	< 8	8 to 13	> 13
90-94	< 4	4 to 11	> 11

Table 3
Agility based training routine

Session 1 to 5	Exercises	Walking based: change of directions, cuts, obstacle crossing, bench balancing. Double leg line jumps, bench step ups
	Duration	~30s per exercise, 2 rounds, 5 exercises
	Variations	Elevated balancing, obstacle height, speed, plane of moment
Session 6 to 10	Exercises	Walking based: change of directions, cuts, obstacle crossing, line balancing, swiss cross and combinations of these. Unstable lunges, ball dribbles.
	Duration	~30 s per exercise, 2 rounds, 7 exercises.
	Variations	Color coding of movement directions, all of the previous
Session 11 to 15	Exercises	Walking based: change of directions, cuts, rotations, obstacle crossing, line balancing, swiss cross and combinations of these. Single leg line jumps, bench step ups, orientation games
	Duration	~30 s per exercise, 3 rounds, 7 exercises
	Variations	Sound coding of movement tasks and directions, walking modes, all of the previous.
Session 16 to 20	Exercises	Walking based: obstacle crawl and crossing, catch through the course, beam balancing, orientation games, hurdling Sprints, lunges, lateral double leg jumps, bench step-ups.
	Duration	~30 s per exercise, 3 rounds, 8 exercises
	Variations	All of the previous
Session 21 to 24	Exercises	Walking based: Song with coded tasks on words, catch through the course, orientation reaction games. Lateral and forward single leg jumps, skipping on unstable surfaces, lunges, ball throw and catch exercises.
	Duration	~30 s per exercise, 3 rounds, 8 exercises
	Variations	Cognitive tasks, ball dribbling while performing the tasks, all of the previous.

Table 4
Traditional agility routine

Session 1 to 5	Exercises	Static balance exercises in double leg stance Squats, calf raises, supported split squats
	Duration	30s exercise,30 s pause,3 rounds,8 exercises
	Variations	Perturbations
Session 6 to 10	Exercises	Static balance exercises in step or tandem stance. Squats, calf raises, side lunges, split squats, crunches
	Duration	50s exercise,30 s pause,2 rounds,8 exercises
	Variations	Perturbations Strength exercises o slightly unstable surface
Session 11 to 15	Exercises	Static and dynamic balance exercises in step or tandem stance Step up, calf raises, side lunges, split squats
	Duration	35s exercise,30 s pause,3 rounds,8 exercises
	Variations	Cognitive tasks, unstable surfaces, arm balance Strength exercises on slightly unstable surface
Session 16 to 20	Exercises	Balance exercise in step on tandem stance Planks, squats, single-leg calf raises, side lunges, split squats, Bulgarian
	Duration	40s exercise,20 s pause,3 rounds,8 exercises
	Variations	Cognitive tasks, perturbations, arm balance
Session 21 to 24	Exercises	Dynamic balance exercises in tandem or single leg stance Squats, single-leg calf raises, step-ups, Bulgarian split squats
	Duration	55s exercise,20 s pause,3 rounds,8 exercises
	Variations	Unstable surfaces, perturbations, arm balance

Step 5 - With every detection, the sit-up counters are incremented for good posture and ignored for bad postures respectively. A sit-up is made up of up and down phases so the final count can be obtained by dividing the number of up-down phases with 2.

Step 6 - Calculation of geriatric score - Once the total count is obtained, we refer to Table 1 and Table 2 to display the result of the test. [13]

Step 7 - Suggest exercise routine according to score - If the user's agility score is below average, the training routine is displayed according to the table given below. [14]

If the user's agility score is above average, a message saying "You seem healthy" is presented. The suggested routine depends on the total sit-up count and includes the exercises, duration and its variations.

5. Results and Discussion

To check the working of our algorithm we perform this test on a 22-year-old female and a 23-year-old male subject. Since this application is made for academic purposes and improved and extension of our previous study [15], we performed the test on young subjects only though the relevance of the application will make more sense if test trials were performed on older subjects.

As shown in the figure, the female subject enters her name, age and gender and starts performing the chair stand test for 30 seconds.

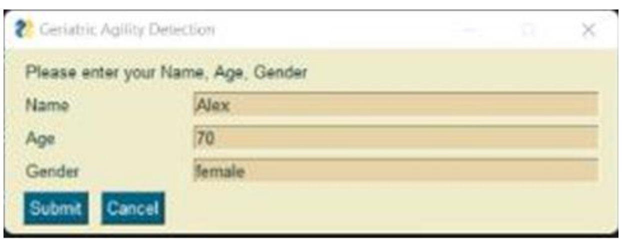

Fig. 6. Input from the user

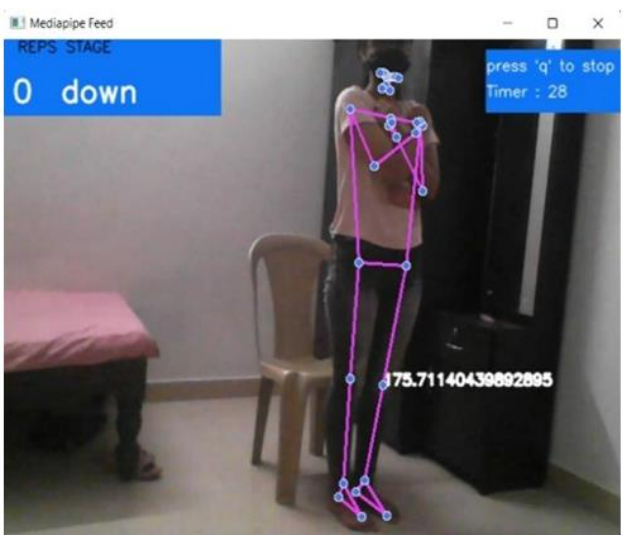

Fig. 7. Test subject during down phase

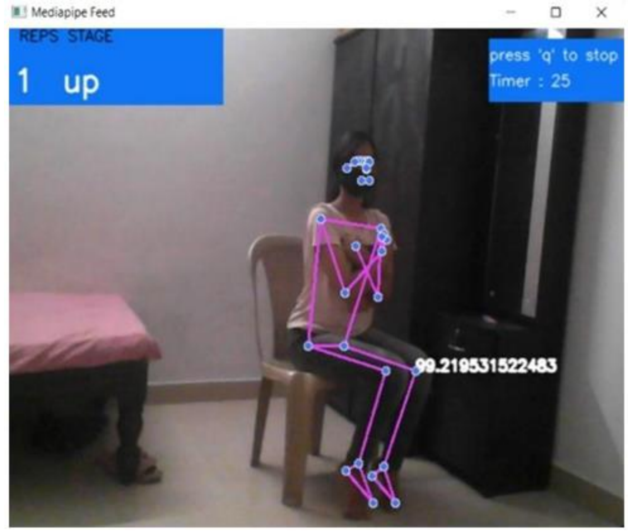

Fig. 8. Test subject during up phase

Fig. 9. Result showing performance feedback

The capturing screen displays the timer to show the number of seconds left and also the number of sit-ups performed. After the test is over, the feedback of how the subject performed the test is displayed as shown in the diagram. Since the subject's geriatric score is above average, we display the message - "You seem healthy!".

In another trial, a male subject performs this test. As shown in the diagram, the application works similarly in this case as well. Since the subject's geriatric score is below average, the screen also displays agility based routine exercises.

We can infer from our trials that Mediapipe can be effectively used for Body Pose detection. The application works fine even with dim light conditions. The output can be interpreted by another user and does not require any technical knowledge or knowledge about how agility detection works in clinical settings.

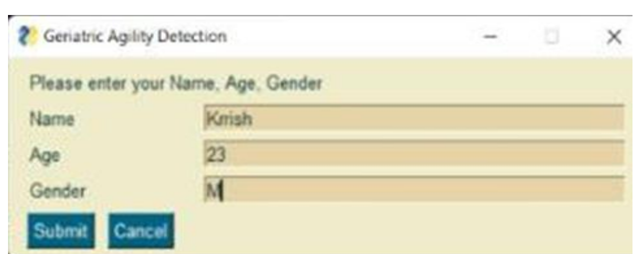

Fig. 10. Input from the user

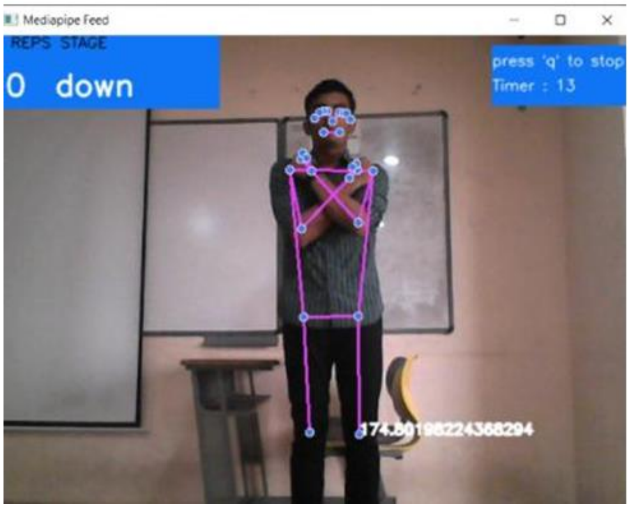

Fig. 11. Test subject during down phase

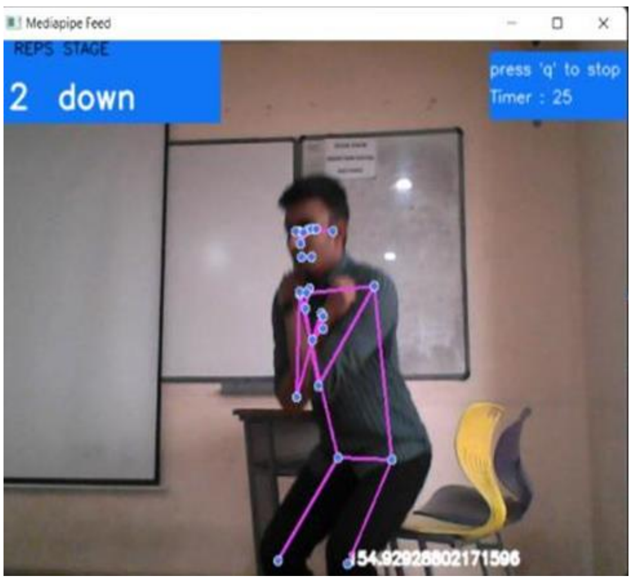

Fig. 12. Test subject during up phase

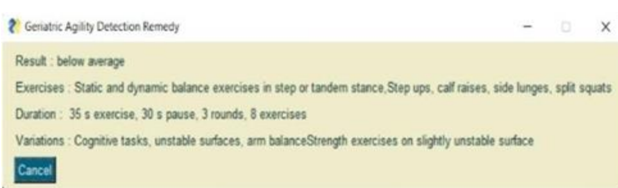

Fig. 13. Result showing performance feedback

6. Conclusion

Detecting and analyzing body language is gaining a lot of attention lately. In applications like measuring physical activities, sign language recognition, and full-body gesture control, human position estimation from video is crucial. It can be used as the foundation for yoga, dance, and fitness applications. For inference, most current state-of-the-art algorithms rely on powerful desktop environments, whereas our method delivers real-time performance on most recent mobile phones, desktops/laptops, in Python, and even on the web. Our application can be used for monitoring workouts without any involvement of a trainer and can help elderly become independent. This application offers features such as real-time analysis, injury prevention and getting best results. The system is limited for workout purposes with single-person compatibility at a time.

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