Mono Camera-based Human Skeletal Tracking for Squat Exercise Abnormality Detection using Double Exponential Smoothing

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Abstract*—Human action analysis is an enthralling area of research in artificial intelligence, as it may be used to improve a range of applications, including sports coaching, rehabilitation, and monitoring. By forecasting the body's vital position of posture, human action analysis may be performed. Human body tracking and action recognition are the two primary components of video-based human action analysis. We present an efficient human tracking model for squat exercises using the open-source MediaPipe technology. The human posture detection model is used to detect and track the vital body joints within the human topology. A series of critical body joint motions are being observed and analysed for aberrant body movement patterns while conducting squat workouts. The model is validated using a squat dataset collected from ten healthy people of varying genders and physiques. The incoming data from the model is filtered using the double exponential smoothing method;the Mean Squared Error between the measured and smoothed angles is determined to classify the movement as normal or abnormal. Level smoothing and trend control have parameters of 0.8928 and 0.77256, respectively. Six out of ten subjects in the trial were precisely predicted by the model. The mean square error of the signals obtained under normal and abnormal squat settings is 56.3197 and 29.7857, respectively. Thus, by utilising a simple threshold method, the low-cost camera-based squat movement condition detection model was able to detect the abnormality of the workout movement.

***Keywords*—Abnormality movement; double exponential smoothing; skeletal tracking; mediapipe; squat exercise**

I. Introduction

Human activity recognition is a critical application in the computer vision community. Human activity recognition is comprised of two primary components: body tracking and action recognition [1]. These two components have garnered considerable attention in recent years as a result of their multiple applications in areas such as health tracking, sign language recognition, and video surveillance.

Human body tracking can be utilised to tackle a range of problems. This includes avoiding injury during physical body exercise routines (aerobic, anaerobic, or agility training) by monitoring and predicting the person's body's vital points through each frame of a video stream [2]. Injury-free is essential during physical exercise. Thus, computer-assisted self-training systems for sports and exercise can help participants improve their performance and avoid injuries [3]. Besides human body monitoring can be used to solve several issues. Injuries can be avoided during physical training (aerobic, anaerobic, or agility training) by monitoring and predicting body vital points through video streams [2]. Injury-free exercising is crucial and computer-assisted self-training systems for sports and exercise can help athletes increase their performance while avoiding injury [3]. Determining the fundamental cause of postural, balance, and total body coordination difficulties can also be done through corrective exercise.

Action recognition can also benefit the living. During the COVID-19 pandemic, Malaysians were advised to stay at home and avoid routine visits. This may harm older people who were not accompanied by youngsters. Due to health difficulties, most elderly people are in danger of falling and fainting. Seniors may also face security issues such as robbery. Moreover, a study found that Malaysian healthcare has improved, accelerating the "Silver tsunami" of population ageing [4]. Thus, eldercare should focus on this population. Using machine learning and contemporary computer vision techniques, we can detect things of interest more accurately than humans [5]. Hence, an automated eldercare system should be considered for good monitoring.

Additionally, numerous studies have demonstrated that commercially available devices such as the Microsoft Kinect Sensor, the PlayStation Eye, and the Wiimote are successful at sensing and analysing human joint motion in many applications [6]. However, these researcher tracking studies necessitated the use of a 3-Dimensional (3D) sensor and additional expensive visual and wearable sensors. As a result, a low-cost mono camera equipped with a MediaPipe algorithm is proposed for determining pose landmarks and monitoring action motion in daily routine human activity.

II. Literature Review

Human skeletal tracking consists of tracking several key points from different parts of the human body, such as the body joints, eyes, nose, and ears depending on the purpose of tracking. The key points are connected creating a human skeletal form. Generally, the tracking of human motion can be done through visual information like images from video or extraction data through camera sensors. From the human skeletal features, Human Pose Estimation (HPE) and Human Action Recognition (HAR) can be applied. HPE is widely

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applied to solve various problems such as bad posture correction, sports movement monitoring, fall detection, etc., [7]. HAR can be used to recognize daily life activities such as running, jumping, squatting, etc. which are recognized from video sequences using the vectors extracted [8]. The goal of HAR is to study and recognize the nature of action from unknown video sequences automatically [9].

A. Human Body and Movement Tracking

Human movement detection predicts and tracks an entity's position and orientation within an image/video frame. Previous researchers have investigated various techniques for detecting human movement. Certain detecting methods make use of wearable sensors. The Inertial Motion Unit (IMU) sensor is one of the most frequently used wearable sensors [10]. IMU technology is used in conjunction with a machine learning (ML) technique to precisely locate body key points and deliver accurate orientation measurements. However, relying exclusively on wearable sensors may impose significant limits, particularly for home-based monitoring. In addition, the implementation of the environmental sensor leads to high costs due to the use of professional external sensors [11].

In comparison to prior systems, some researchers use depth cameras such as the Kinect sensor, a low-cost consumer-grade 3D camera, to extract key points on the human body [12]. This technology can contribute to the provision of several human action characteristics, such as depth, colour differentiation, and human skeletal structure [13]. The x and y coordinates, as well as the confidence value, were recorded for each body key point, and a 2-Dimensional (2D) human movement estimate can be performed using the OpenPose algorithm [14]. Human movement detection can also be performed with an RGB stereo camera as a result of enhanced advances in in-depth imaging technology [6].

B. Machine Learning Framework

A framework represents an interface algorithm that makes the work of the machine learning model easier and faster. [7] apply six machine learning frameworks; OpenPose, Tflite, Pifpat, Tfjs (mobileNet), Tfjs (Resnet 50), and BlazePose for pose estimation and correction of fitness training dataset since the goal was to find the fastest and most accurate methods that work in real-time. Besides that, the use of a Kinect sensor to extract the skeletal features has also been used to determine the abnormality of squat exercise from a dataset [12]. In addition, [15] and [16] suggested the use of the OpenPose framework to extract the keypoints coordinates from the RGB data for pose detection of fall action. In comparison, the BlazePose framework that was used by the MediaPipe model presented a topology with 33 human body keypoints, which is more than OpenPose and Kinect topologies, which only provide 17 human body keypoints [2].

MediaPipe is an open-source ML model purposely for live and streaming media and provides direct and customizable Python solutions as a prebuilt Python package [17]. The primary use of MediaPipe is the quick creation of perceptual pipelines with any models and other reusable components [18]. MediaPipe offers several solutions such as MediaPipe Face Detection, MediaPipe Hands, MediaPipe Pose, MediaPipe Object Detection, etc. MediaPipe Hands tracking solution offers an ML pipeline that includes two different models that act in tandem; Palm Detection Model and Hand Landmark Model [19].

Furthermore, The MediaPipe Pose model, which was inspired by Leonardo's Vitruvian man, can identify the human body by predicting the midpoint of the human's hip, the radius of a circle circumscribing the full body, and the inclination angle of the line linking the shoulder and hip midpoints [18]. In [7] the author applied the MediaPipe Pose solution, which can predict 33 3D human body landmarks for human pose assessment and correction with an emphasis on fitness training. The MediaPipe Pose solution was also used during the pre-trained pose estimate for data collection of various yoga poses [20].

C. Rehabilitation Exercise

Physical therapy and rehabilitation programs are critical for persons who participate in sports, are accident victims, or are senior citizens. Nowadays, rehabilitation programs are conducted prior to the occurrence of any sports injury in order to prepare the athletes for the next level of physical demands [21]. The rehabilitation approach will involve exercises to increase muscle and joint range of motion. To ensure a consistent recovery outcome, patients are urged to complete a series of prescribed home-based physiotherapy sessions.

Squats are a well-known rehabilitation exercise, particularly for people with knee difficulties or injuries. This exercise is ideal for a home workout program because it does not require any extra equipment. Squat exercises require the patient's knee and hip joints to flex and extend to develop the body part's flexion and extension strength [22]. Hip, knee, and ankle movements must be synchronized correctly to ensure efficient muscle function and avoid damage throughout the activity [23]. The squat exercise cycle is performed as followed:

Step 1: Stand straight, open your feet align with the shoulder, and stretch out your arms to the front;

Step 2: Bend down your knees slowly until you reach a half-crouched position while maintaining your chest upward and back straight;

Step 3: Hold the previous step position for approximately one second while maintaining your feet flat on the floor;

Step 4: Slowly stand up to the initial position and one cycle is completed;

Step 5: Repeat steps 1 to 4.

All of the procedures above must be followed precisely to guarantee that the exercise's objective is met and that undesired injury is avoided. The training and testing phases of this paper make use of a similar squat dataset from [14]. The dataset was created by video recording squat exercises performed by ten healthy volunteers of varying gender and body build using Microsoft Kinect. The dataset is divided into two distinct categories: normal and aberrant. The normal condition dataset contains somewhat slow squatting movements to mimic the patient's gradual movement during rehabilitation. While the abnormal dataset was conducted with the same group of volunteers performing a comparable squat exercise with only one leg. This is done to mimic the same level of discomfort experienced by some patients during therapy.

III. METHODOLOGY

The goal of this research is to identify the abnormality of squat exercise by a single human using a single camera image. Training and testing datasets for classifiers were acquired from a set of ten subjects with different genders and physical body postures performed half-squat exercise. The diversities of human squat exercise were classified into two categories; normal condition squat and abnormal condition squat as shown in Fig. 1.

The normal condition squat consists of ten videos of the different subjects performing double legs half-squat exercise as shown in Fig. 1(a). On the other hand, the abnormal condition squat videos consist of ten videos of a similar subject in normal condition squat performing single legs half-squat exercise as shown in Fig. 1(b). Each subject conducted the exercise separately, and it was captured from front viewpoint angles in normal lab lighting. In this study, the distance between the 3D image sensor and subjects is fixed in the range of 2.5-3 meters.

A. Human Skeletal Tracking-MediaPipe Pose

MediaPipe Pose is the current solution for human pose assessment i.e. fitness training [12] which can predict 33 3D human body landmarks as shown in Fig. 2. By using the MediaPipe Pose model, this study is improvised and able to track the subjects' lower body (from hip to ankle) of the squat exercise dataset without the use of any marker on 2D images.

Fig. 1. Normal and Abnormal Squat Exercise Posture Steps [10].

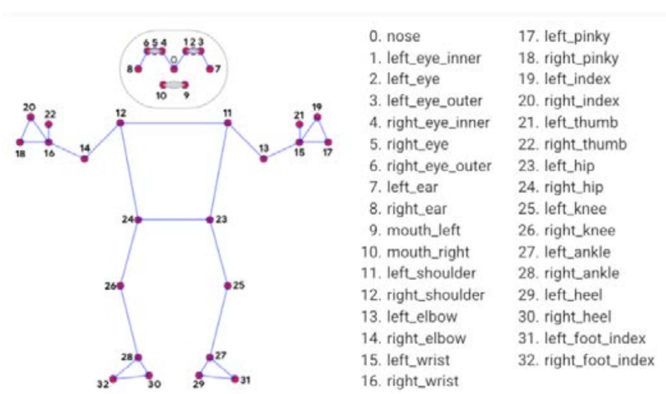

Fig. 2. Thirty-Three Human Skeletal Landmarks of MediaPipe Pose Model.

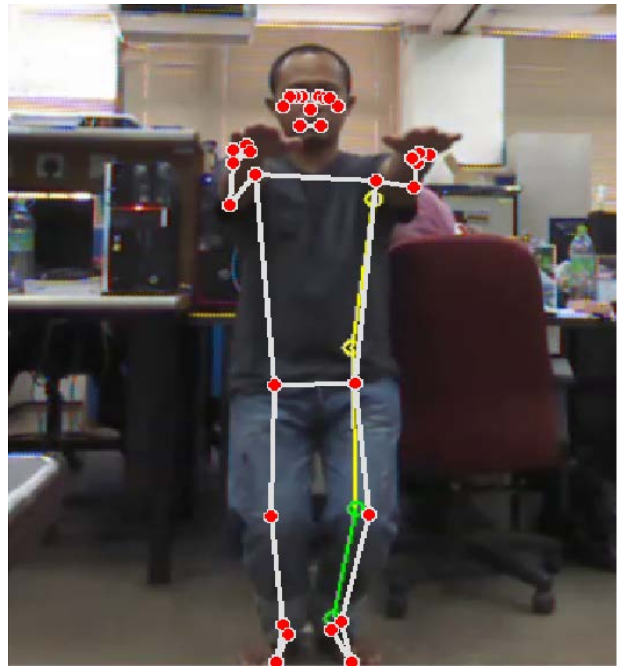

Fig. 3. Thirty-Three 3D Body Landmarks-MediaPipe Pose on 2D Image.

The study focuses on the hip-knee-ankle of a subject performing the half-squat exercise. The MediaPipe Pose model is capable to predict the essential human body landmarks as shown in Fig. 3.

B. Joint Angle Tracking

The angle was generated in 3D space based on the joint's coordinates as shown in Fig. 4. Euclidean distance is computed to evaluate the distance between two joints; hip-knee joint, knee-ankle joint, and knee-hip joint [24] using (1)-(3) below:

$$d_{HL,KL} = \sqrt{(x_{HL}-x_{KL})^2+(y_{HL}-y_{KL})^2+(z_{HL}-z_{KL})^2} \quad (1)$$

$$d_{KL,AL} = \sqrt{(x_{KL}-x_{AL})^2+(y_{KL}-y_{AL})^2+(z_{KL}-z_{AL})^2} \quad (2)$$

$$d_{AL,HL} = \sqrt{(x_{AL}-x_{HL})^2+(y_{AL}-y_{HL})^2+(z_{AL}-z_{HL})^2} \quad (3)$$

From the distance calculated, the knee angle (θ), is determined by using the Law of Cosines in (4) as stated below:

$$\theta_K = \cos^{-1}\left(\frac{d_{HL,KL}^2+d_{KL,AL}^2-d_{AL,HL}^2}{2d_{HL,KL}d_{KL,AL}}\right), 0 \le \theta_K \le \pi \quad (4)$$

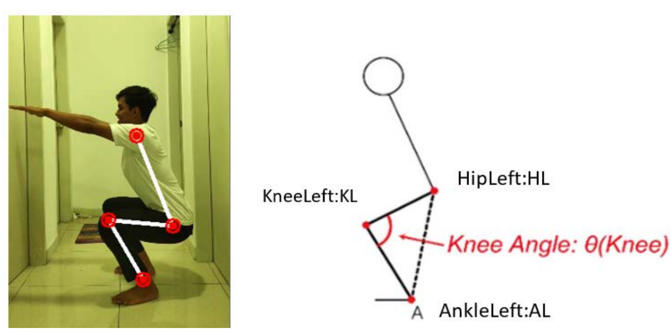

Fig. 4. Illustration of Tracking Lower Body Joints and Joint Movement.

C. *Signal Filtering*

From the result of the hip-knee-ankle angle extracted from the skeletal features, it is discovered that there was some unwanted noise presented. This random noise might occur due to the image parameter such as illumination disturbance, random shadow, subject pose, etc. from the dataset [12]. Therefore, an algorithm is applied to filter the incoming data image for the elimination of the noise before proceeding to the next process.

Double Exponential Smoothing (DES) was chosen for the following task as suggested by [25] to predict the trend for forecasting. Generally, DES is approached in economic data analysis to predict the immense range of noise, to forecast a trend, and give high forecasting accuracy level. DES also has been proven to run 100 times faster than the extended Kalman Filter [26]. The (5)-(6) are applied as stated below which are related to DES:

$$S_t = \alpha y_t + (1 - \alpha)(S_{t-1} + b_{t-1}) \,, \alpha \in [0,1] \tag{5}$$

$$S_t = \alpha y_t + (1 - \alpha)(S_{t-1} + b_{t-1}) \,, \alpha \in [0,1] \tag{6}$$

where:

y_t = original measured angle.

α = level smoothing parameter.

S_t = smoothed value.

b_t = trend control parameter.

β = trend smoothing parameter.

Equation 5 is applied for adjusting the new smoothed value (S_t) by totaling the previous smoothed value (S_t-1) with the previous trend control (b_t-1). Equation 6 is responsible for updating the new trend control (b_t) by calculating the difference between current S_t with S_t-1. In this study, the initial value of S_t and b_t are $S_1 = y_1$ and b1 = $y_2 - y_1$; similar to the method applied by [10]. All the angles' data of the 10 samples are recorded and smoothed using DES. Fig. 5 represents one of the examples of DES application on the original angle data and the result of the smoothed value. It shows that smoothed using DES is able to reduce the random noise due to environmental constraints.

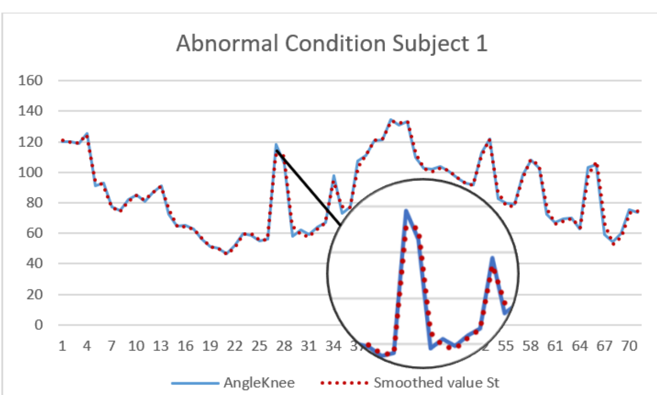

Fig. 5. Original Angle Vs Smoothed Angle Data.

Next, the mean squared error (MSE) is calculated from the smoothed value of the knee angle by the DES method [25]. The MSE method is used to determine the values of constant that minimizes the error size and how close estimations or forecasts are to actual data. The MSE formula can be defined in (7) below:

$$\text{MSE} = \frac{1}{n}\sum e_t^2 \tag{7}$$

Where the error, e, is derived from the difference of values between the current period of the original measured angle (yt) and the previous period of smoothed value (S_{t-1}) as shown in (8).

$$e_t = y_t - S_{t-1} \tag{8}$$

In this study, to calculate the MSE value for all samples of the normal and abnormal conditions, the average value is calculated. The optimum α and β values of 0.8928 and 0.77256 respectively are reused based on performance results obtained by [10].

IV. Result

Based on the experimental setup explained in Section II, Fig. 6(a) shows the half-squat exercise in normal conditions, while Fig. 6(b) shows half-squat exercise in abnormal condition performed by subject 1. The hip-knee-ankle angle was extracted from the squat exercise performed by subject 1 in normal conditions (Fig. 7) and abnormal conditions (Fig. 8).

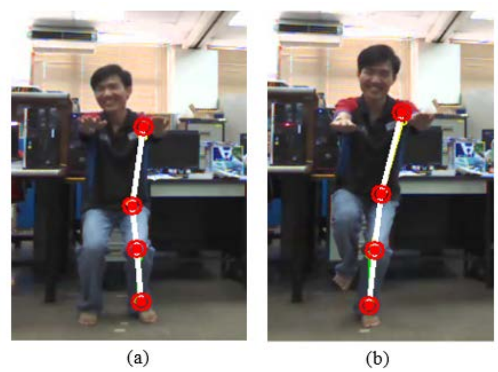

Fig. 6. Half-Squat Exercise in Normal (a) and Abnormal (b) Conditions.

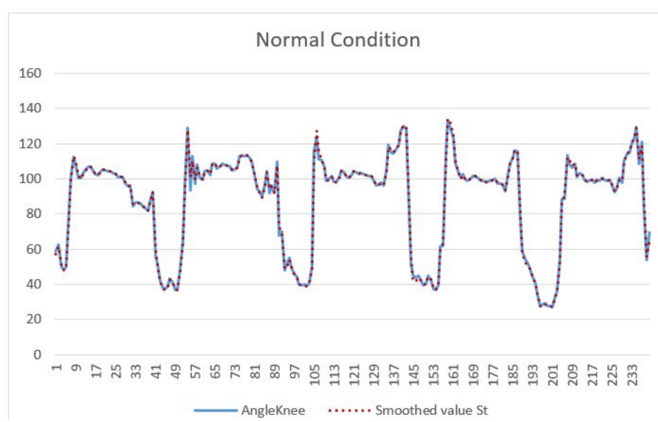

Fig. 7. Knee Angle Captured from Normal Squat Exercise for Subject 1.

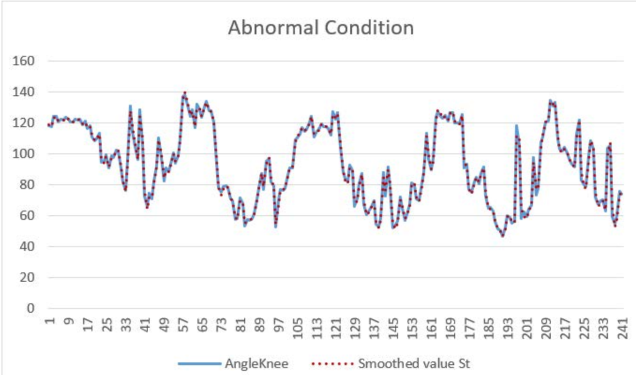

Fig. 8. Knee Angle Captured from Abnormal Squat Exercise for Subject 1.

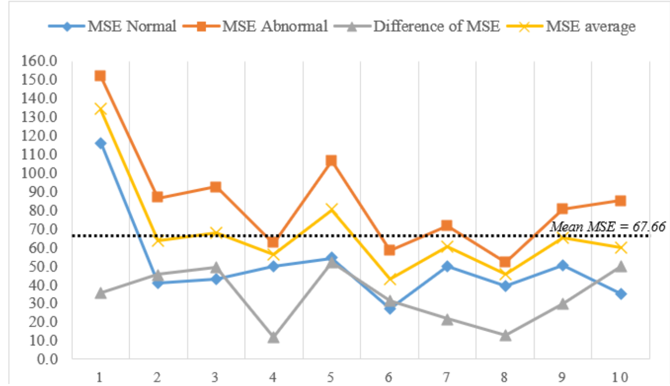

Fig. 9. MSE for Normal Vs Abnormal Squat Condition.

Based on the data that have been collected from the dataset in Table I, there is a significant difference between the result of MSE of the normal and abnormal conditions. The average of MSE from 10 normal exercise data is 50.63, for the specified constants: $\alpha = 0.8928$ and $\beta = 0.7726$. In contrast, the average MSE for ten abnormal exercise data sets is 84.69.

The comparison of MSE normal and abnormal conditions, the difference between MSE, and the average of MSE among the subjects are presented in Fig. 9. From the figure, subjects 4 and 8 performed adequate accurate movements during both normal and abnormal squat exercises in comparison to the other subjects. This shows that their positions are balanced during both normal and abnormal exercise. In contrast, squat exercise movement of subjects 5 and 10 can be considered mediocre based on the difference between the MSE of normal and abnormal. The threshold value of 67.66 (mean MSE) meets as a dividing boundary between the normal and abnormal conditions for all subjects except subjects 1, 4, 6, and 8.

TABLE I. THE PERFORMANCE RESULT FOR EACH SUBJECT

Subject No.	**Mean Squared Error**			
	Normal	***Abnormal***	***Difference***	***Average***
1	116.40	151.83	35.43	134.11
2	40.94	86.45	45.51	63.69
3	43.25	92.61	49.36	67.93
4	50.13	62.12	11.99	56.12
Subject No.	**Mean Squared Error**			
	Normal	***Abnormal***	***Difference***	***Average***
5	54.18	106.29	52.16	80.24
6	27.14	58.48	31.33	42.81
7	49.73	71.50	21.77	60.62
8	39.16	52.25	13.08	45.71
9	50.42	80.33	29.91	65.38
10	34.95	85.04	50.09	59.99
Mean	**50.63**	**84.69**	**34.06**	**67.66**
Min	**27.14**	**52.25**	**11.99**	**42.81**
Max	**116.40**	**151.83**	**52.12**	**134.11**

V. DISCUSSION

From Fig. 7 and Fig. 8, the trend in MSE of the normal condition has a lower frequency of vibration compared with the abnormal condition. This showed that the subject was able to maintain a better squat form while performing the exercise in normal conditions compared to an abnormal condition. This proves that MSE is a suitable measurement for evaluating the performance of the system [27]. The smoothed value also helps in evaluating the data by reducing the noise. Thus, the simulated result shows that the DES method has been proven as one of the methods to reduce random noise from the original data of the dataset based on the computed results [28]. As a result, from Table I, the average MSE for normal condition squat exercise is lower and better than the abnormal condition. This shows that the MediaPipe Pose model able to predict the 3D body landmarks of subjects efficiently [12].

Fig. 9 shows that their positions are balanced during both normal and abnormal exercise. In contrast, squat exercise movement of subjects 5 and 10 can be considered mediocre based on the difference between the MSE of normal and abnormal. The threshold value of 67.66 (mean MSE) meets as a dividing boundary between the normal and abnormal conditions for all subjects except subjects 1, 4, 6, and 8.

There are some limitations of the model observed in this research that need to be considered and further addressed. Firstly, beside its high ability to perform human detection of squat action, MediaPipe Pose algorithm has so far only managed to detect a single person per frame. It may not be not suitable to be used for human detection of squat action when multiple humans present in the image frames. In addition to that, the model faces difficulties if there are obstacles blocking the camera's view of human upper body. This will affect the human detection confidence level. To address this issue and to have better detection performance, it is advisable to ensure that no foreign object block the camera view. Lastly, like other vision system issues, the performance of human detection might be affected due to the lack of proper illumination.

VI. CONCLUSION

This paper introduced the use of the MediaPipe Pose model for human movement tracking on a 2D frame-frame video dataset. The MediaPipe Pose model is a powerful model which can predict thirty-three 3D human body landmarks and can be used to perform a human virtual skeletal model for features extraction. Skeletal pose features will contain all of the necessary information to comprehend the action's results. This model can be applied to a rehabilitation center or self-monitoring exercise at home. DES method was able to minimize the random noise from the tracked angle data that might be due to the image parameter such as illumination, shadow, pose, etc. Next, MSE is applied to evaluate the movement cycle for squat exercise. Finally, the mean MSE was used as the threshold value to differentiate the posture movement for squat exercise between the two conditions.

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