IDENTIFICATION AND ANALYSIS OF HUMAN PHYSICAL EXERCISE POSTURES USING COMPUTER VISION AND DEEP LEARNING

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FACULTY OF ENGINEERING
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IDENTIFICATION AND ANALYSIS OF HUMAN PHYSICAL EXERCISE POSTURES USING COMPUTER VISION AND DEEP LEARNING

ABSTRACT

The ability of the human beings to perform physical exercise postures is identified by the unique ways and its important categories are gait analysis and muscle expansion of the human body as exercise performance. The postures performed by the human beings are estimated in a dynamic way. Most current systems which are employed for identifying human exercises propose complex systems. The advancement of the Artificial Intelligence broke the existing complexities, identifies, and analyze the human exercise without complex models. The effectiveness of the Computer Vision and Deep Learning are used to monitor the accurate exercise postures of every human gait to solve the trainer's vacuum in the exercise environment. In this paper, it has evaluated and developed customized pose model to identify correct human physical postures, to analyze the correct form of physical exercise in a correct way in all type of exercise environments. For correct comparison, typical nodal points are identified (depends on exercise type) from the human body to calculate the estimations in a synchronous way. The estimations are nodal analysis which replicates the correct analyzation. The input frames of nodes are obtained by Webcam to a computer which makes the identification dynamic and naturalistic as Human-Computer interaction. We propose Deep pose estimation model to improve the analyzation of the physical exercises without complex systems. The results demonstrated the possibility of non-invasive identification which can be used for certain physical exercise postures using simple system with better accuracy.

Index Terms: Physical Exercise, Computer Vision, Deep Learning, Pose estimation

MENGENALPASTI DAN MENGANALISIS POSTUR LATIHAN FIZIKAL MANUSIA MENGGUNAKAN VISI KOMPUTER DAN PEMBELAJARAN DEEP

ABSTRAK

Keupayaan manusia melakukan postur latihan fizikal dikenal pasti dengan cara yang unik dan kategorinya yang penting adalah analisis gaya berjalan dan pengembangan otot tubuh manusia sebagai prestasi latihan. Postur yang dilakukan oleh manusia diperkirakan secara dinamik. Sebilangan besar sistem semasa yang digunakan untuk mengenal pasti latihan manusia mencadangkan sistem yang kompleks. Kemajuan Kecerdasan Buatan mematahkan kerumitan yang ada, mengenal pasti, dan menganalisis latihan manusia tanpa model yang kompleks. Keberkesanan Penglihatan Komputer dan Pembelajaran Dalam digunakan untuk memantau postur senaman yang tepat dari setiap langkah manusia untuk menyelesaikan kekosongan pelatih di persekitaran latihan. Dalam makalah ini, ia telah menilai dan mengembangkan model pose yang disesuaikan untuk mengenal pasti postur fizikal manusia yang betul, untuk menganalisis bentuk latihan fizikal yang betul dengan cara yang betul dalam semua jenis persekitaran latihan. Untuk perbandingan yang betul, titik nod khas dikenal pasti (bergantung pada jenis senaman) dari tubuh manusia untuk mengira anggaran secara serentak. Anggarannya adalah analisis nod yang mereplikasi analisis yang betul. Rangka input node diperoleh oleh Webcam ke komputer yang menjadikan pengenalan dinamik dan naturalistik sebagai interaksi Manusia-Komputer. Kami mencadangkan model estimasi Deep pose untuk meningkatkan analisis latihan fizikal tanpa sistem yang kompleks. Hasilnya menunjukkan kemungkinan pengenalan non-invasif yang dapat digunakan untuk postur latihan fizikal tertentu menggunakan sistem sederhana dengan ketepatan yang lebih baik.

Syarat Indeks: Latihan Fizikal, Penglihatan Komputer, Pembelajaran Dalam, Pose anggaran

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS AND ABBREVIATIONS

AI	:	Artificial Intelligence
CNN	:	Convolutional Neural Network
BCI	:	Brain Computer Interaction
RCS	:	Remote Control System
DTW	:	Dynamic Time Warping
VGG	:	Visual Geometry Group
FCN	:	Fully Connected Network
CPU	:	Central Processing Unit
GPU	:	Graphical Processing Unit
IDE	:	Integrated Development
ROI	:	Region of Interest

LIST OF APPENDICES

CHAPTER 1: INTRODUCTION

1.1 Background

The aim of the proposed research work is to develop and implement the AI model which can do identification and analysis of human physical exercise postures using Deep Learning and Computer Vision in actual scenarios. The research is proposed for the selected exercises like curls, squat, side leg rise, side lounges, wall stand, fire hydrants, step up, yogic squat, jack knives, knee crunches, pushups, semi pushups, full plank, and elbow plank. The physical exercises are the part of human rehabilitation process which can be performed at all possible situations for relaxation.

With reference to the World Health Organization, one third of the world population are not doing proper exercise practices which leads to the physical instability and impacts huge on the fitness of the human being World Health Organization (2020). To support this statement the pandemic has worsened the exercise situations. People are really in need of an application which can support and motivate them to do exercises at their own without external factors like Gym, Trainers, and so on. The need of personal trainer application arises with the solid goal to train themselves in the existing situations. This Application will interact instantly according to the postures performed by the user in all the possible exercise environments. The merits of Deep Learning and Computer Vision will help to solve the exercise identification and analysis for this application of research for the mentioned exercises.

There are certain technology limitations like full body tracking and real time node image processing (more detail in Chapter 2). Recently, Google's MediaPipe framework can track the full body nodes (33 points) on the human body from a computer or phone camera in actual scenarios. MediaPipe is a commonly available open-source framework released

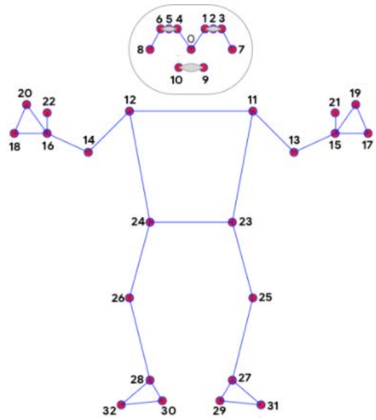

Figure 1.1: Blaze Pose Model Topology

by Google in August 2019 which is widely used for AI techniques like object tracking, face recognition and multi-node tracking on human body, and so on.

By applying the merits of the MediaPipe, the Blazepose model as shown in Figure 1.1, is used to track the body nodes and postures from a normal camera connected to the processor and detect gestures with a Convolutional Neural Network (CNN) in real time. The node detection is depending on the Blazepose model, and this research work is focused on developing the AI model to do the exercise posture analyzation and Blazepose model is a successive tool for identification of human body nodes. The uniqueness of the proposed work is simplicity of the system which uses one camera from a processor and then a developed computer application is capable of all the analytical work for the human exercises.

The proposed research work complies with time and other limitations which does not intend to be done analyzation for the all the exercises done at the exercise environments.

This work identifies and analyzes fourteen different exercises and provides good hypothesis that similar practice can be performed to analyze other exercises in a larger scope.

1.2 Problem Statement

There are many individuals conducting physical exercise without the knowledge of the right postures. This proposed work helps person to identify and analyze their physical exercise posture using simple and interactive system which will be user-friendly. The analyzation will instantly show the accuracy of the exercise postures and suitable counting for the exercises performed using the dashboard. This project aims to solve the identification problems of people who are performing physical exercise. The identification and analysis of the physical exercise done by humans are performed by using deep learning models. The deep neural networks are trained to work as like the trainers in the gym to help the human beings to perform physical exercise effectively.

1.3 Objectives

The objectives of the research are:

1. To create an Intelligent system using deep learning model to identify human physical postures.
2. To develop a computer vision model to analyze the correct form of physical exercise.
3. To propose an AI system which can assist the users to perform the physical exercise in the correct way.

1.4 Scope of Study

Even though the proposed work is designed for the exercise posture analysis, there are some important limitations which are not took up as research constraints. For instance, it is not possible to analyse all the exercise postures without user's selection. In this project user will select the listed exercises before performing it. It's a complicated work, if exercise is done without prior selection because of mixing of the same gesture actions of the exercises. The different combinations of nodes from BlazePose model are used to analyse the exercises. The selection of the node is important feature of the analyzation. The implementation of the concept is done by the Python tool and TensorFlow framework based on Graphical Processing Unit (GPU).

1.5 Summary

The thesis is organized as follows. Chapter one illustrates the background of this project, as well as the problem statement, project objectives and scope of work. Chapter two gives an overview of and a detailed literature review of object detection and Exercise Posture detection. Chapter three indicates the research methods to conduct this task. Chapter four presents the results of the proposed method and result discussion. Chapter five concludes the whole thesis and points out possible future works for this project.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter will discuss the earlier research works, before this proposed work, conducted by various authors who all tried to recognize various objects and pose modules in the human body to find postures with the unique approaches. The features of this proposed work will represent the comparison works which are related to Google's MediaPipe Framework, and establishments of all other possible approaches to recognize exercise postures and the uses of the different systems in people's everyday life.

2.2 Computer Vision approaches for Object Detection

Computer Vision approach is the one of the most used technologies that presents gave the best results for the tasks like object tracking, contour detection, edge detection, image processing, image segmentation, machine vision counter actions and so on. The OpenCV is an early relied open-source library technology developed by the Intel, and it focuses fully on the real time compute vision related projects.

There are many research works done prior to the node analyzation of the human body parts. The study proposed by (Silver & Xin, 1997) has tracked dynamic turbulent 3D features random datasets. Figure 2.1 shows color amalgamation of the different object in simulation set. The important feature of the algorithm is the Boolean set characteristics to make computer vision system for acquiring 3D visualization. This work shows solid proof dynamic tracking of the objects in the different frames acquired by the camera.

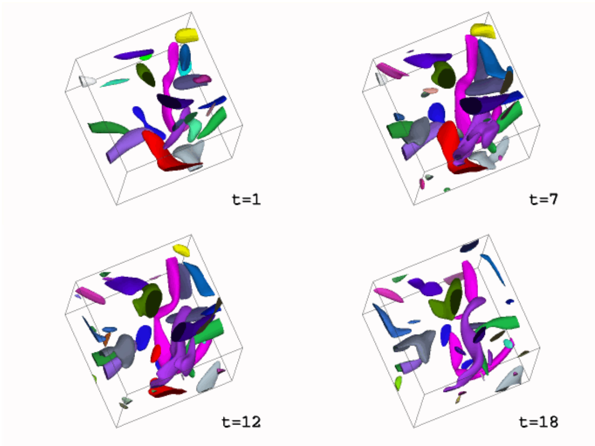

Figure 2.1: Simulation of coherent Structures

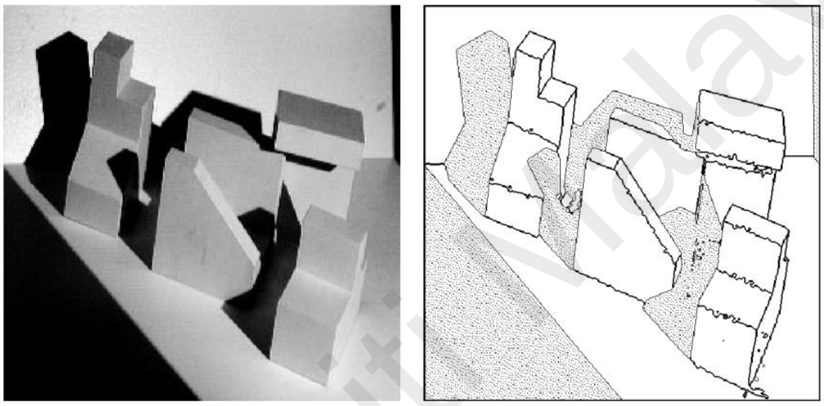

Figure 2.2: Segmentation of the testing image

Another research work proposed by (Ohya, Kosaka, & Kak, 1998) has its own navigation robot which uses single camera for computer vision and ultra-sonic sensors to support the system to obtain the objectives. The model developed by (Ohya et al., 1998) non-stop navigation position correction system to monitor the obstacle before the prototype robot. This concept clearly shows computer vision calculations like edge detection, positioning, 3D model can be used for self-assuring autonomous systems. Similarly, the work done by (Frigui & Krishnapuram, 1999) has a new approach called Robust Competitive Agglomeration (RCA) to cluster the different object patterns. This approach has many merits in robust classification feature to identify the objects. Figure 2.2 shows the image segmentation of the certain objects. The feature classification is based on the correct detection, over segmentation, under segmentation, and noise cross.

Another work proposed by the (Kim, 1999) has computer vision assisted calibration system which works on the weighted least square error algorithm to update the 3D model from the sequence of the video frames from the camera module. The (Kim, 1999) shows the dynamic correction of the patterns of the 3D models in the vision system. Figure 2.3 shows the operators of the algorithm shows that the initial coarse matching is interactive. The similar work done by (Kocak, Lobo, & Widder, 1999) is used for classifying and tracking the bioluminescent plankton under the sea water which is useful for oceanographers. This work firmly shows the features can be sorted easily by computer vision techniques for sequence of video frames. Figure 2.4 shows the tracking of the plankton in the few iterations of the image processing. The system uses active contouring models for labelling, tracking, and segmenting the image set of the bioluminescent planktons.

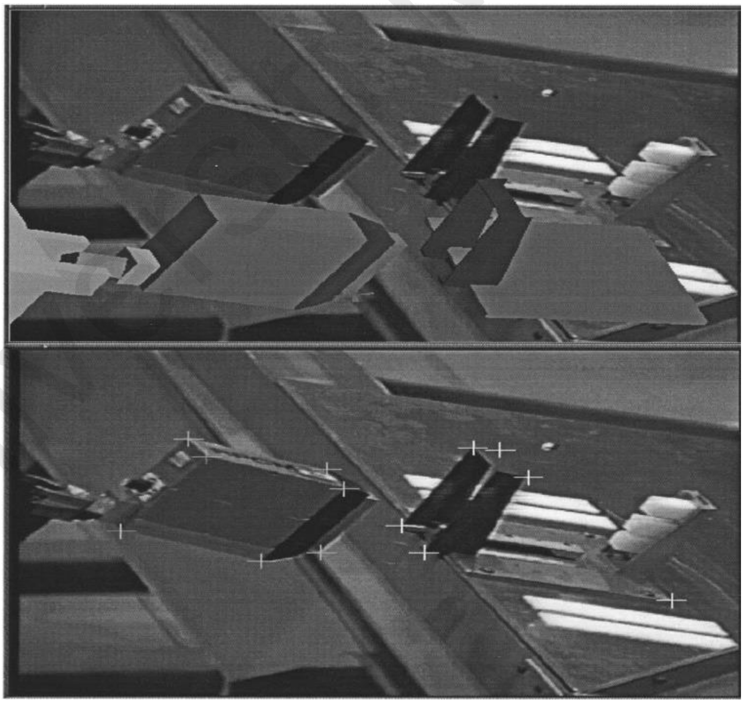

Figure 2.3: Initial coarse matching

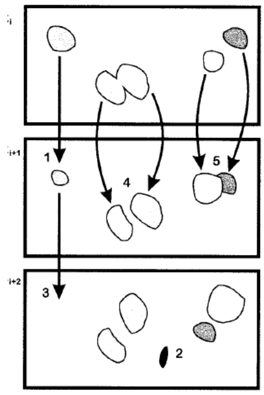

Figure 2.4: Segmentation based Morphological Characteristics

Another research work done by (Alegria & Serra, 2000) calibration system for the analog and digital measuring systems in the laboratory. The proposed work demonstrates image analysis algorithm for the analysing instrument reading. The system set the threshold for identifying the position of the needle of the analog instruments. Similarly, the digital instruments are identified using angle calculations of the differences among the digits at certain coordinates. This work proves to use edge detecting, image subtraction and scale processing techniques are useful for the accurate application like instrument reading measurement. In addition, the algorithm proposed by (Engbers & Smeulders, 2003) has the simplified pattern recognition algorithm for identifying large scale image in sequences. The sequences are acquired by the computer vision techniques like invariance, multiple interpretations of the edge patterns, and robust probabilistic analysis of the image as shown in Figure 2.5.

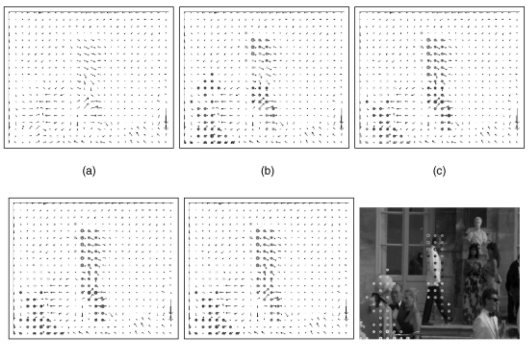

Figure 2.5: Intermediate results shows tracking of the object

The system developed by the (Trivedi, Shinko Yuanhsien, Childers, & Krotosky, 2004) has the unique sensory system and vision-based algorithm to release air bags in the car. The experiments cover different sitting patterns of the passengers inside the car. The algorithm senses the dynamic attributes to perform classification action for releasing the airbags in the real time system. The system consistently proposes the integration of the manual signal and computer vision system together to build the applications. However, the proposed work (Tyrrell, LaPre, Carothers, Roysam, & Stewart, 2004) also introduced the virtual device driver to establish the offline computer vision algorithm to identify defect on the eye surface in the ophthalmology surgery. The work properly invents the integrating the computer vision algorithms without writing huge data codes repeatedly to the system. This established work simplifies deployment of the vision system on the kernel processors. Similarly, the work done by the (Sofou, Evangelopoulos, & Maragos, 2005) shows Soil image segmentation system and texture analysis system using computer vision approaches. This concept implementation verifies the remote sensing automation process. The texture analysis as shown in Figure 2.6, done by image variations in the soil surface modulations with multi frequency spatial modulation.

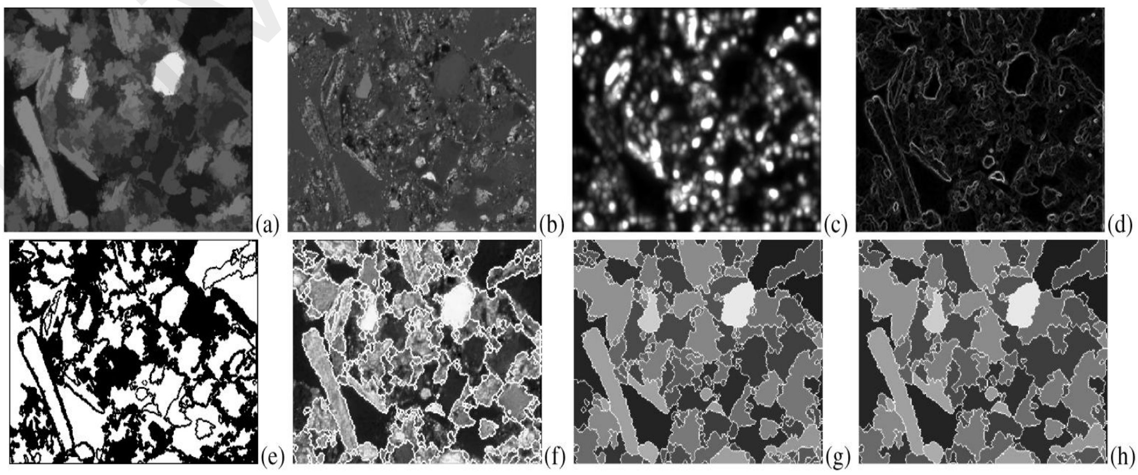

Figure 2.6: Soil segmentation results

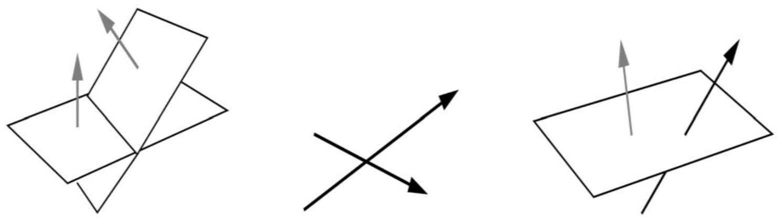

Figure 2.7: Angel relations in model

Another research work performed by (Xufei, Kanungo, & Haralick, 2005) Error propagation statistical method for the identifying the positions of the building edges. This methodology acquits angle of the spatial models from the image captured by the camera. The patterns in the algorithm dynamically recognise the 3D parameters in the image which built by the error propagation method. Figure 2.7 shows the spatial angle calculation of the model. The work accomplished by the (Pun, Alecu, Chanel, Kronegg, & Voloshynovskiy, 2006) have Brain Computer Interaction (BCI) system which connects the Electro Encephalogram (EEG) through the system to develop computer vision model. The model uses EEG signals which direct proof of physiological signs which cannot be faked. The important aspect of the proposed work by (Pun et al., 2006) is physical signs were optimized for developing human interactive computer vision system. Similarly, the results of the research work by (Lee & Park, 2009) for developing Remote Control System (RCS) model uses human hand moves for establishing control system. This system detects finger counting based on the contour model designed in the flow process. This helps the user to control the systems with simple hand gestures before sitting in front of the camera module. Figure 2.8 shows the iterative results of the finger counting used for RCS.

The frame less event-based system for fast vision technique developed by (Perez-Carrasco et al., 2010) has unique of identifying features from the video frames. The conventional method using convolution method to extract features for texture recognition was boycotted and special sensory system was designed for finding classification, implementation of the event-based system reduces computational process for 25-30 frames of video images, and event based sustains to enhancing features for the classification as computational efficient computer vision system. Likewise, the work achieved by the Google AI blog (2020) used non-linear diffusion analysis to filter the micro nucleus organisms. The non-linear filtering allows the algorithm to perform seed evaluation to segment the organisms and this technique further intensifies the clustering data. Figure 2.9 shows the filtered image of the organisms.

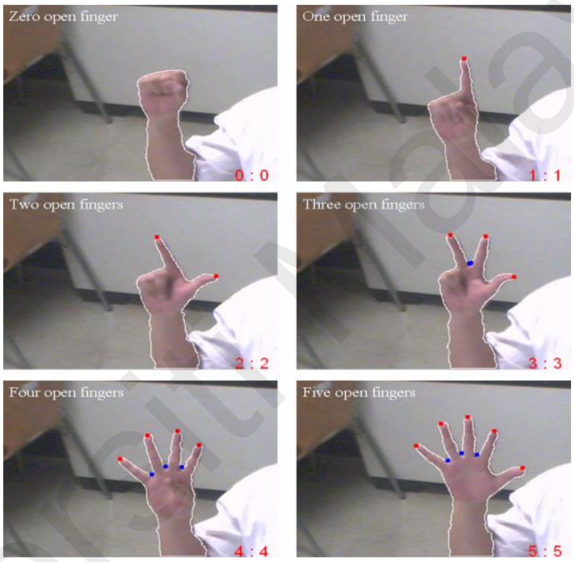

Figure 2.8: Example of finger counting

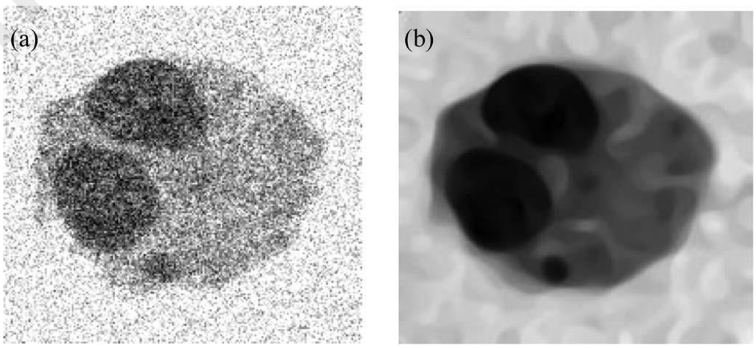

Figure 2.9: Non-linear filter image of micronucleus

2.3 Approaches for Exercise Detection

The human body metabolism is enhanced by performing the process of physical exercise postures and relaxes the body for rehabilitation (Bakar, Samad, Pebrianti, Mustafa, & Abdullah, 2015). The physical exercises can be performed based on the flexibility of the human beings. The flexibility attained during the performance of the physical exercises will improve the muscle functionalities. Evidently, the exercises are performed based on the gait movements, depends on the level of difficulty, and every exercise has dissimilar body nodes to analyze based on the gait action (Kavian & Nadian-Ghomsheh, 2020). The gait action based on the movements of the exercise can be evaluated by selecting correct nodal action of range for each exercise. The selected body nodes for the certain exercise will have clear unique line of records (Kavian & Nadian-Ghomsheh, 2020). The identification of the exercises performed by humans are identified by the Gait activity of the exercise (Z. Zhang, Wang, & Cui, 2018). The gait activity of the exercise will have the specific curve-fit characteristics naturally. The possibility of the gait activity recognition rate for the nodal analysis is attained by the linear analysis of the image (Tao, Li, Wu, & Maybank, 2007). The Figure 2.10 shows the averaged gait image of the same person after the linear analysis of the image from the database.

Figure 2.10: Averaged gait images

(Tao et al., 2007) performed the possibilities of Tensor Discriminant Analysis for classifying the gait of the human by processing sequence of images. Another research work done by (Yang, Li, Zeng, & Wang, 2021) have the two branches of CNN for the node recognition to perform pose estimation for developing open pose detection method. Although, the methodology of nodal post estimation by the open pose detection method gives the fine results, they failed to analyze the exercises in dynamic way. Figure 2.11 shows the enhanced view of the pose estimation without analyzation and human-computer interaction. The existing systems, for deeply analyzing the posture of the exercises are done with the use of certain externally fitted system like Radio Frequency Identification (RFID) modules, Wi-fi signal routers, Image sensor, accelerometer, gyroscope and so on (Z. Liu, Liu, & Li, 2020) (Ermes, PÄrkkÄ, MÄntyjÄrvi, & Korhonen, 2008) (Mekruksavanich & Jitpattanakul, 2020; Nagarkoti, Teotia, Mahale, & Das, 2019) (W. Zhang, Su, & He, 2020). (Z. Liu et al., 2020) performed the monitoring of the Human physical exercises with the heavy act kinetic camera, RFID tag system, transceiver, reader/writer, and processor which is the complicated system than that of human pose estimation system (Yang et al., 2021). The Figure 2.12 gives the design of the complicated system proposed by (Z. Liu et al., 2020).

Figure 2.11: enhanced view of Open Pose

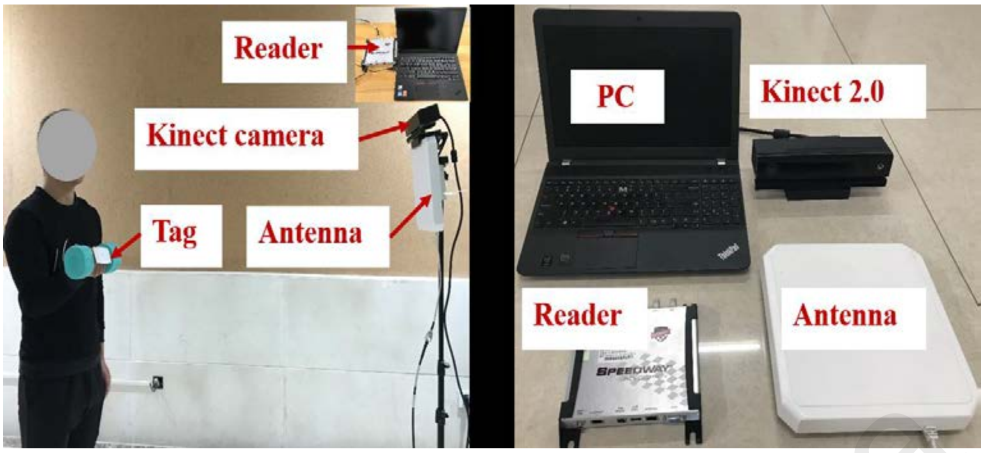

Figure 2.12: Complicated experiment layout

The computerized recognition of human physical exercises analyzation is possibly done by the help of computer vision (Ar & Akgul, 2014). The results achieved by both (Z. Liu et al., 2020) and (Ar & Akgul, 2014) are optimized to get good results and exercise analyzation was attained with complex designs. The advancement of the open-source computer vision gives better results for effectively analyzing the exercises using Remote rehabilitation process (Schez-Sobrino, Vallejo, Monekosso, Glez-Morcillo, & Remagnino, 2020). The developed the rehabilitation process as gamified interactive system (Schez-Sobrino et al., 2020). Figure 2.13 shows the dynamic exercise analyzation system for the stroke patients.

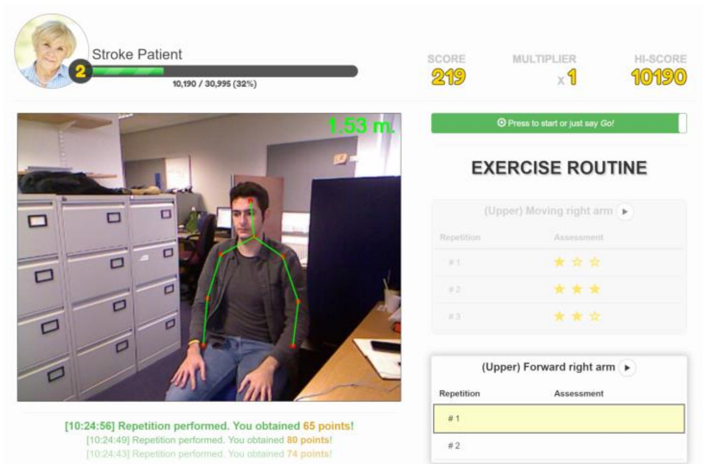

Figure 2.13: Gamified system for rehabilitation process

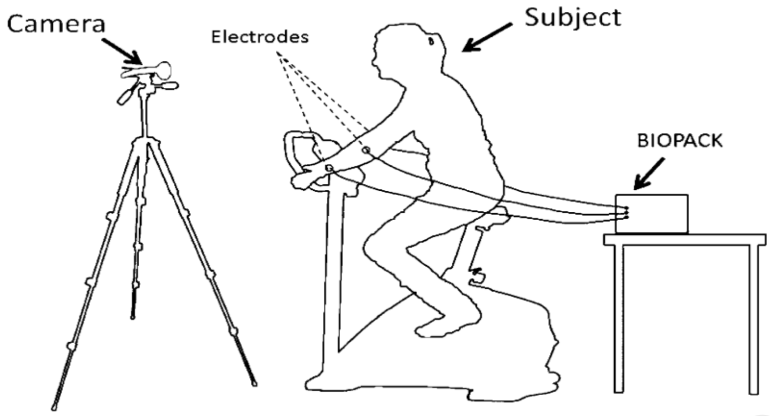

Figure 2.14: Non-invasive experimental setup

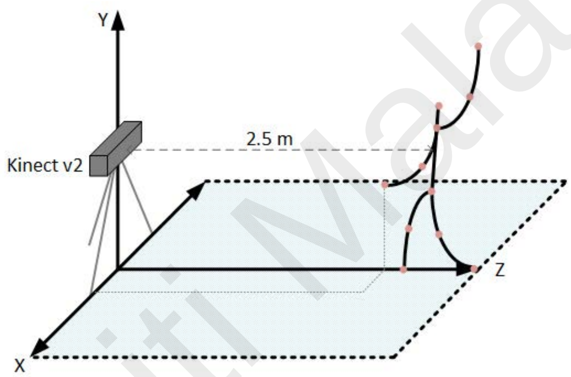

Figure 2.15: Enhanced view of Open Pose

The system can produce optimal results when it uses DTW algorithm to get the exercise pattern from the patients (Schez-Sobrino et al., 2020) (Schez-Sobrino, Monekosso, Remagnino, Vallejo, & Glez-Morcillo, 2019). The assessment done by (Schez-Sobrino et al., 2020) promotes remote rehabilitation with 3-D transformation (Posture and rotation). (Schez-Sobrino et al., 2019) engraved exercise rehabilitation for stroke survivors without the interactive counting performance feature. Remote and contactless recordings of all physical human signals will directly enroot health application (Monkaresi, Calvo, & Yan, 2014). (Monkaresi et al., 2014) proposed a contactless heart rate monitoring system using Webcam. Figure 2.14 shows the experimental view of the study for implementing machine learning approach of contact less heart rate monitoring. The image acquisition, processing and feature extraction using a webcam simplifies the complex system design (Yang et al., 2021) (Monkaresi et al., 2014). The motion capture recognition for human exercises is possible with the skeletal data of the motion (Vox & Wallhoff, 2017). The (Vox & Wallhoff, 2017) done a classification of few exercises using SVM architecture, but model normalized the output with mixed pattern of exercise recognition ended up with loss of accuracy. Figure 2.15 shows the skeletal data acquisition through the kinetic camera. The evaluation for few knee exercises can be spontaneously acquired to attain the performance using histogram analysis (Pattamaset, Charoenpong, & Charoensiriwath, 2020). (Pattamaset et al., 2020) performed axis segmentation pattern to classify the skeletonization of the typical exercise. Figure 2.16 shows the histogram analysis for knee movement of the exercise. The disadvantage of automatic system proposed by (Pattamaset et al., 2020) ends up with reduced overall accuracy due to complicated axis extension calculations. The tracking of physical counteractions can also be done by routing Wi-Fi module system (N. Liu, 2017). (N. Liu, 2017) proposed a Wi-gym framework which requires coverable transmitting capabilities at exercise environment to pre-train the accuracy and complexity of system of will increase computational loss for many exercise classes. Similarly, CNNs for exercise recognition and classification enforces strong pattern label as input for the calculations (Bakchy et al., 2018; Huang et al., 2020; Rungsawasdisap et al., 2019).

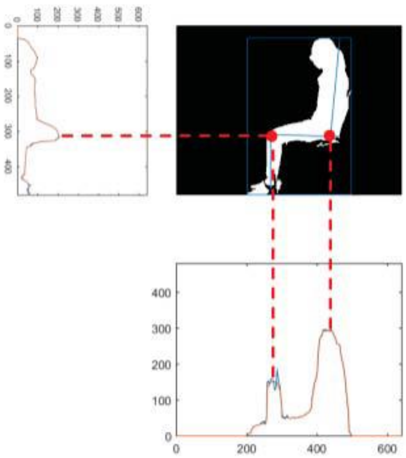

Figure 2.16: Histogram analysis of binary image

2.4 Pose Estimation Methods

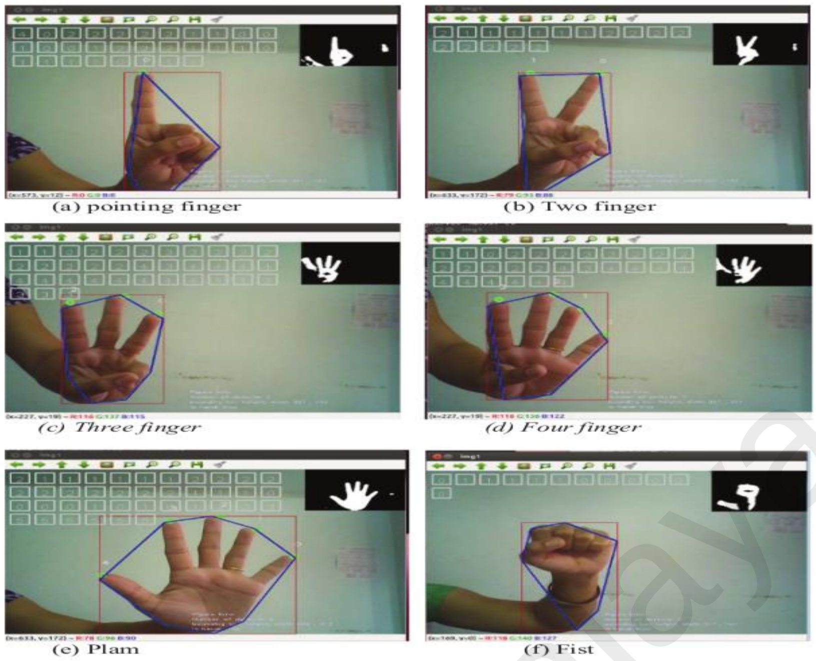

Figure 2.17: Contour detection of open hand

The contour detection is key feature for the most computer vision works approaches as discussed in earlier works. The detection of contours possibly gives good results in classifying, tracking, and identifying the objects. Although, the contour detection has been nice approach, further robust technique is required which focuses on real time computer vision applications.

The contour detection generates unusual identification of problems. First, it is challenging behind all combination of postures to identify the exercise postures of the humans. Second, if we have forms of the different postures, we cannot detect the posture at the correct blob, at the actual analyzation position. In addition to that, the processing acquires more images as many frames acquired by the camera.

The model proposed by the (Gurav et.al,2015) clearly shows that the hand postures for steady signs detection is done, which cannot be used for the clear posture attainments. Figure 2.17 clearly shows the steady signs of hand and its contrast image. Even though, the camera acquires the image at the speed of 30fps, the concept of contour detection syncs and gives better output on the contrasted background and the object which is tracked for the contours need to be close to the camera.

In this research, computer vision and deep learning methods are used for identification and analyzation of physical exercises. The proposed system follows certain line of action (nodes) by BlazePose model Google AI Blog (2020) of the human body parts to analyze the exercise. The selected device is merely a normal webcam to capture video input to take depth data of exercise.

2.5 Overview of Blazepose Model

Pose estimation of human body from a certain action of gestures plays vital role in identifying the physical nodes and enables quick learning process in the applications of augmented reality, human body gesture control method, sign language recognition and for quantifying the human physical exercise postures. The BlazePose is a Deep Learning model which can detect the node topology in difference appearances, environments, degree of flexibility, mixtures of postures and so on.

2.5.1 Topology of Blazepose Model

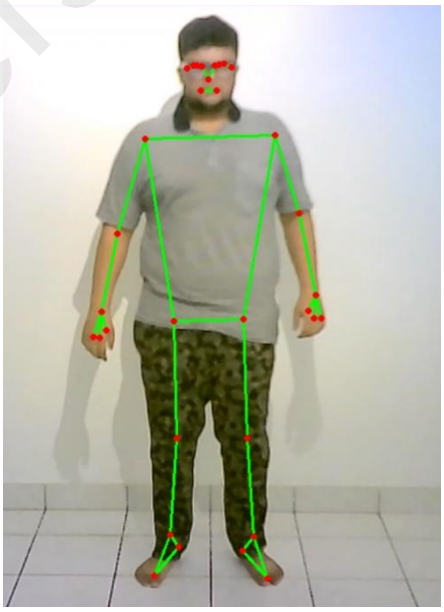

Figure 2.18: Topology of BlazePose model implemented in human pose

The topology of 33 points from the human body are taken as nodes for reference in this work. These nodes allow to predict the poses alone which gives good results across human model in accordance with number of frames per second. Figure 2.18 shows the implementation of topology of the BlazePose model in human body.

2.5.2 Implementation of Tracking Model

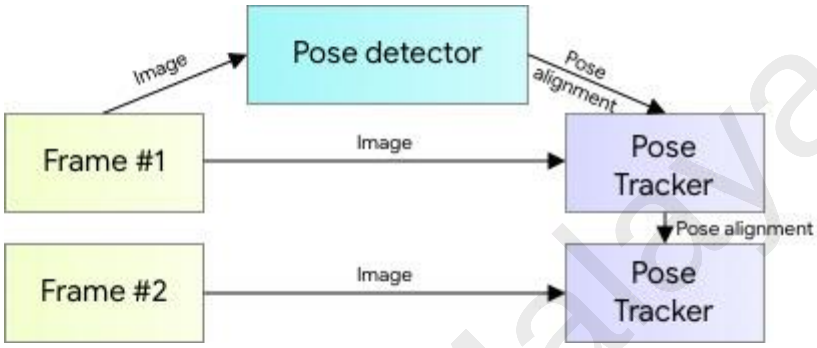

Figure 2.19: Pipeline of tracking model

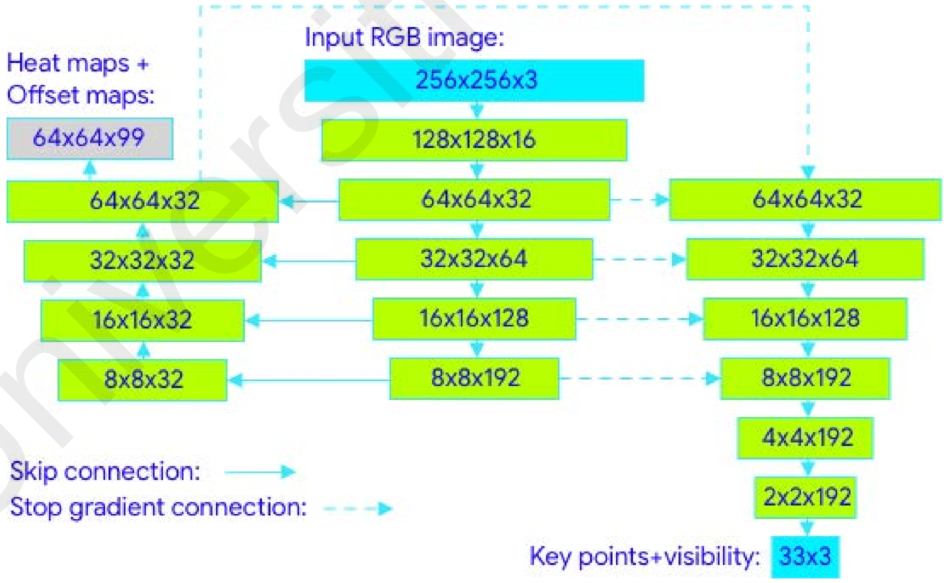

Figure 2.20: Architecture of System

Figure 2.19 explains the pipeline of the tracking model. The images acquired by the camera module will be analyzed by the pose detector calculation, based on the calculation up on the image the pose alignment is shifted as output. The pose tracking is performed and aligned for every image frames. The predictions of the pose detector are done based on the heatmap function combined with regression algorithm. The entropy loss of the function is expressed as:

$$l = \frac{1}{N}\sum_{N=1}^{N}\sum_{i=1}^{W}\sum_{j=1}^{H}\left[p_{ij}^{n}\log p_{ij}^{\hat{n}} + \left(1 - p_{ij}^{n}\right)\log\left(1 - p_{ij}^{\hat{n}}\right)\right] \quad \text{.....................} (1)$$

Figure 2.20 explains the architecture of the tracking model with the heat map, offset function maps establishments, along the convolution process of the input RGB image from the camera, and the process establishment the regression analysis through the image. The regression output of the nodes at all locations of the human body is expressed as following loss:

$$l = \frac{1}{N}\sum_{N=1}^{N}\sum_{ij}\left\|\widetilde{M}n\,(i,j) - Mn(i,j)\right\|^{2} \text{...} (2)$$

Based on the human pose, the implementation of BlazePose model produces better results for estimating the nodes. These nodes are further used for the identification and analyzation of the exercise postures for this proposed research work.

2.6 Software and Hardware

The implement of the BlazePose model requires CPU and GPU hardware. The CPU and GPU are the commonly used hardware modules used for deployment of deep learning model and computer vision techniques. GPUs are high speed computing embedded hardware used for processing tensors. GPUs executes blocks faster than the CPU. Besides the hardware, software is required to deploy the proposed models. The software and IDE are necessary thing for any tool to develop models. The software like Python and its IDEs will allow efficient open-source packages which are used for implementing deep learning applications. The Python version of 3.7.2 and Pycharm Community Edition 2020.2.3 IDE is used for implementing the proposed exercise analyzation work.

The important packages used are TensorFlow, Keras, MediaPipe, OpenCV, Numpy, Math functions, Tkinter, time, Image TK, Img.

2.7 Summary

This chapter discussed different approaches of computer vision and other deep learning techniques for identification and analyzation of object tracking, pose estimation and sign detection. Subsequently, this chapter also explains overview of the BlazePose model and its architecture's outline for better identification of human pose. Then, this chapter also gives the idea about model implementation using available hardware and software with current technological points.

CHAPTER 3: METHODOLOGY

3.1 Introduction

This chapter explains the architecture of the implemented system, nodal point selection for each exercise and implementation of exercise analyzation using computer vision technique.

3.2 Architecture of the System

The proposed system consists of a number of blocks of work. The Figure 3.1 shows the standard functional block diagram of the simplified system. The following part explains the importance of the few blocks of the system.

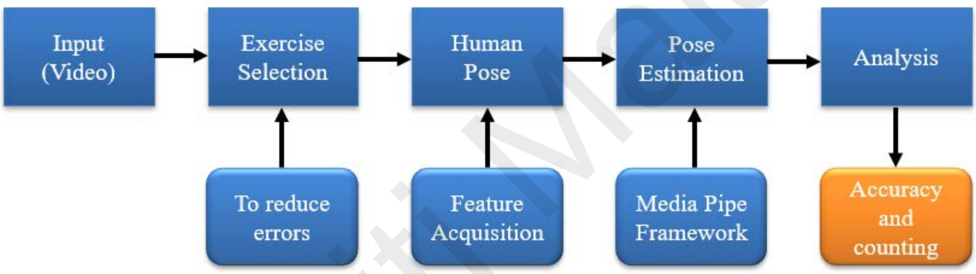

Figure 3.1: Architecture of proposed system

3.2.1 Input

The input for the system is video frame images. The RGB image input is used by the deep learning model to track the nodes. The users are needed to do exercise in the correct form in front of the video capturing object (camera or webcam). The camera should be placed in a good lighting condition. The system can work typically on the exercise environments. The system cannot predict output except when the ROI of human pose is not covered in the view of the computer vision machine. The system gives better analyzation results when frame rate of the camera is minimum 30 fps.

3.2.2 Feature Extraction

The exercises which are selected for analysis will have mixture of postures which cannot be predicted or analyzed without selection particular exercise before performing it. The exercise should be selected by the user from the dashboard of the system. The system can identify and analyze the exercises without errors. The user should know the pre-requisite of performing knowledge of the exercise.

3.2.3 Pose Estimation

The pose estimation is performed with the help of the MediaPipe framework, a deep learning model. The BlazePose model from MediaPipe will identify the nodes of human pose. The framework of the model supports to display 33 points as its features. The proposed will recognize all the 33 points. The customized node selection was done for each exercise. These nodes are used to estimate the exercise postures for analyzation.

3.2.4 Analysis

Pose estimation is only performed with the selected nodes from the customized BlazePose model. The minimum of two or three nodes are packed together for each exercise. The nodes play major role for the exercise analyzation process. The key points are the coordinates of each node in every frame of the video image frames. The coordinates will change dynamically for every frame according to the action of the human pose. These coordinates are used to calculate the two important features angle and distance.

3.2.5 Accuracy and Counting

The selection of key points and other condition based on the exercise we are estimating the accuracy. Based on the accuracy the counting is performed. The counting technique is not same for all the exercises. The exercise like Wall Stand, Full Plank, and Elbow Plank follows timer counting method and other exercises will follow increment counting method.

3.3 Angle Calculation between Nodes

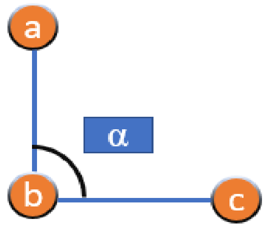

Figure 3.2: view of Angle calculation between nodes

To calculate the angle, three nodes are bundled together. The combination of nodes for angle calculation is picked up based on the exercise pattern and some exercise will have more than one angle. The coordinate points (x_a, y_a) (x_b, y_b) (x_c, y_c) are used to find the α in Figure 3.2. The equation for calculating the angle (α) is expressed as:

$$\alpha = (\mathrm{atan}(y_c - y_b), (x_c - x_b) - \mathrm{atan}(y_a - y_b), (x_a - x_b))\ldots\ldots\ldots\ldots\ldots(3)$$

The negative angle indication is eliminated due to the error of negativity. The error of negativity is eliminated by performing ($\alpha + 360^{\circ}$) calculation, this will help the system to analyze the right form of the exercise.

3.4 Distance Calculation between Nodes

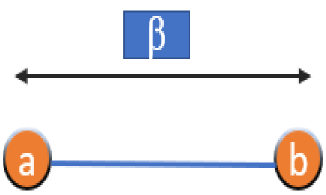

Figure 3.3: view of Angle calculation between nodes

To calculate the distance, two nodes are bundled together. The combination of nodes for distance calculation is selected based on the exercise pattern and some exercise will have more than one distance. The coordinate points (x_a, y_a) (x_b, y_b) are used to find the β in Figure 3.3. The equation for calculating the distance (β) is expressed as:

$$\beta = \sqrt{(y_a - y_b)^2 + (x_a - x_b)^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(4)$$

Now, the α and β are calibrated to α_1 and β_1 to find error range of the exercise by a threshold Ʈ. Ʈ will be defined based on instances of the exercises which is defined for estimating the accuracy of the performed exercise. The critical condition for each exercise is expressed as:

$$1 \geq \alpha_1 \text{ (or) } \beta_1 \geq Ʈ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

The posture experimentation used to define Ʈ for each exercise. The accuracy and counting will be calculated based on the Ʈ.

3.5 Node Selection for Exercises

The node selection for exercises is based on the angle and distance calculation between nodes. The nodes are selected comparing to correct posture of the exercise. The selection of nodes for each exercise after performing many trial and error postures of the exercise postures in the experimentation process. The following figures shows the view of the key point selection for every exercise.

Figure 3.4: Node selection for Squat

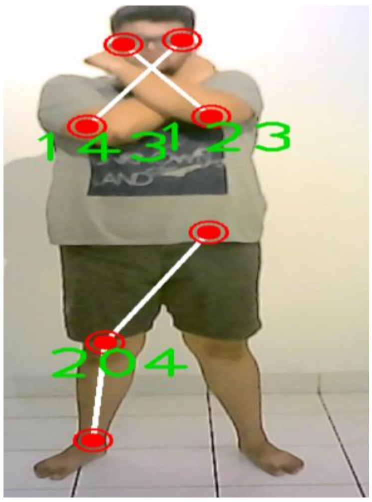

Figure 3.5: Node selection for Yogic Squat

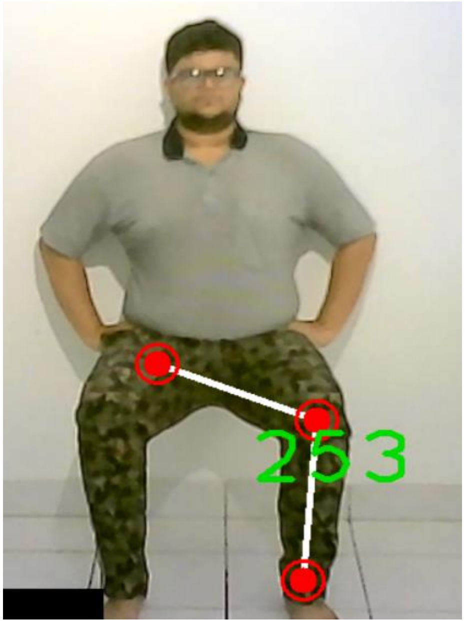

Figure 3.6: Node selection for Wall Stand

Figure 3.7: Node selection for Step-up

Figure 3.8: Node selection for Curl

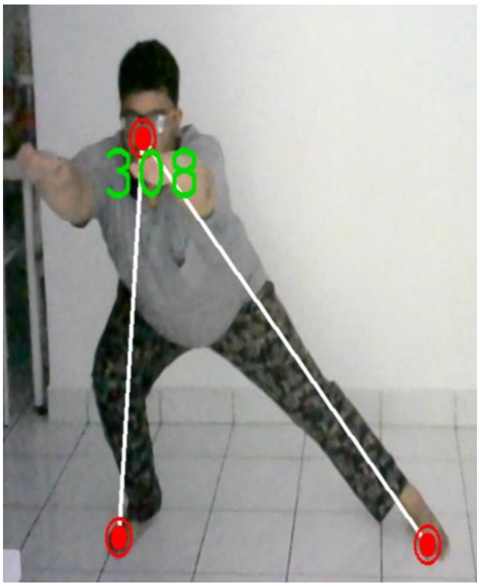

Figure 3.9: Node selection for Side Lounges

Figure 3.10: Node selection for Right Fire Hydrants

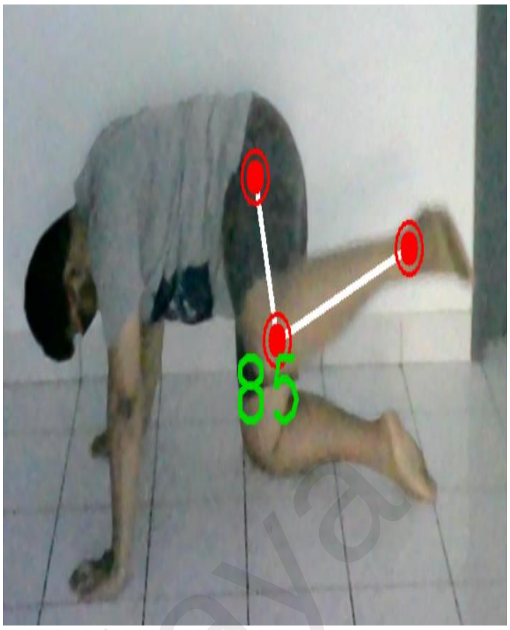

Figure 3.11: Node selection for Left Fire Hydrants

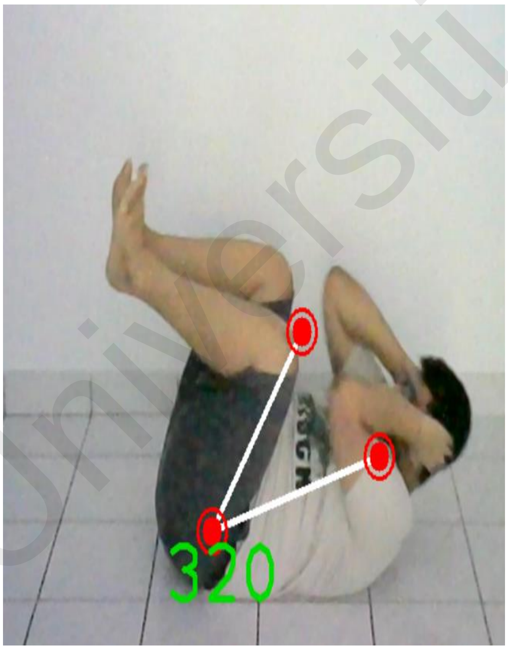

Figure 3.12: Node selection for Knee crunches

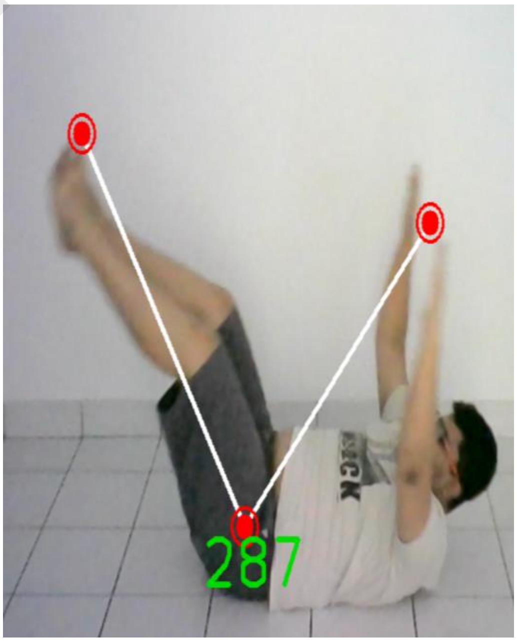

Figure 3.13: Node selection for Jack Knives

Figure 3.14: Node selection for Right Leg Rise

Figure 3.15: Node selection for Left Leg Rise

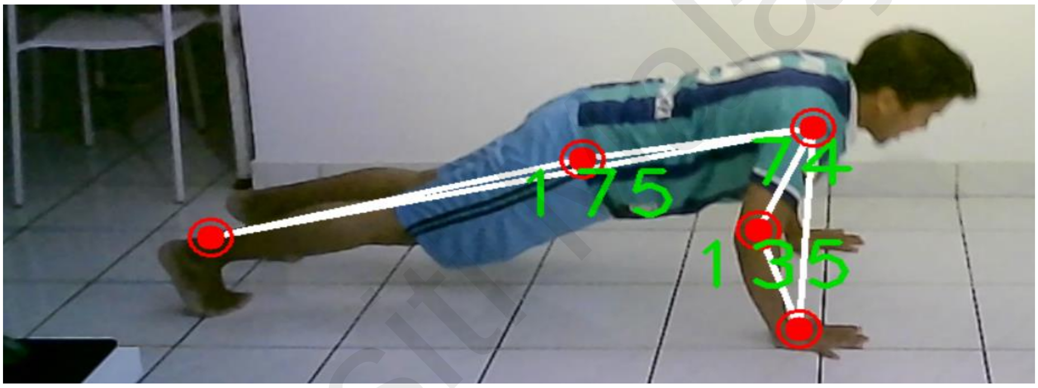

Figure 3.16: Node selection for Push-up

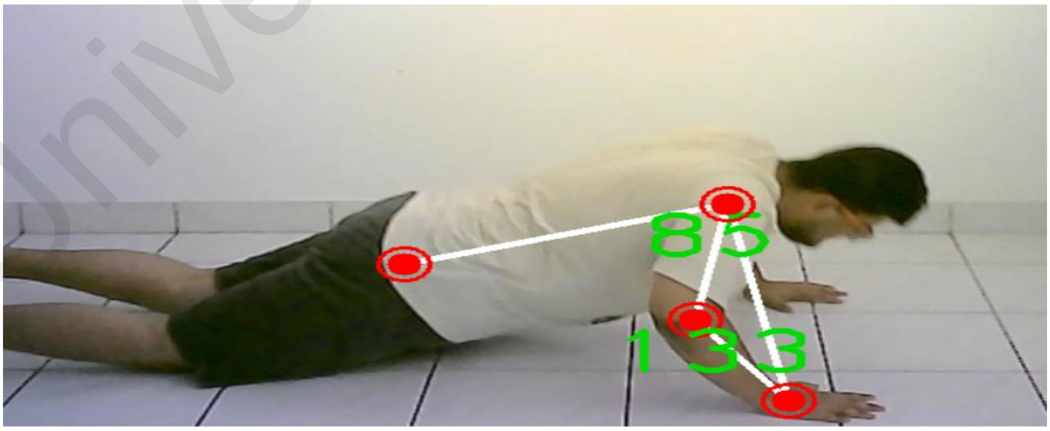

Figure 3.17: Node selection for Push-up

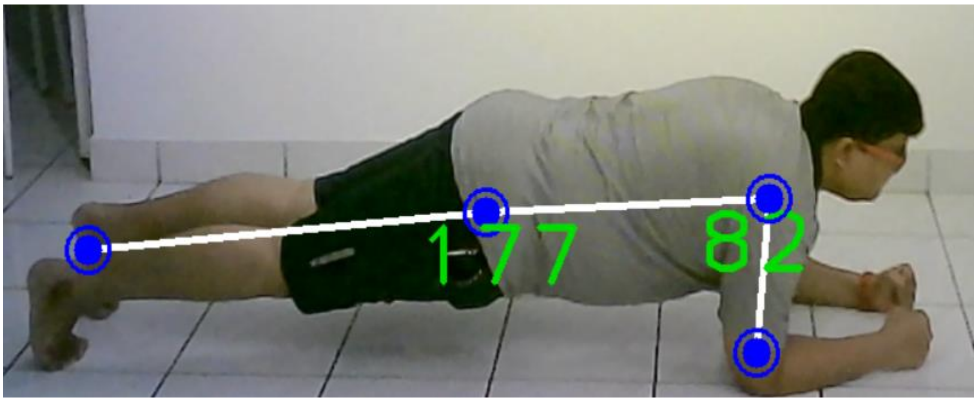

Figure 3.18: Node selection for Elbow Plank

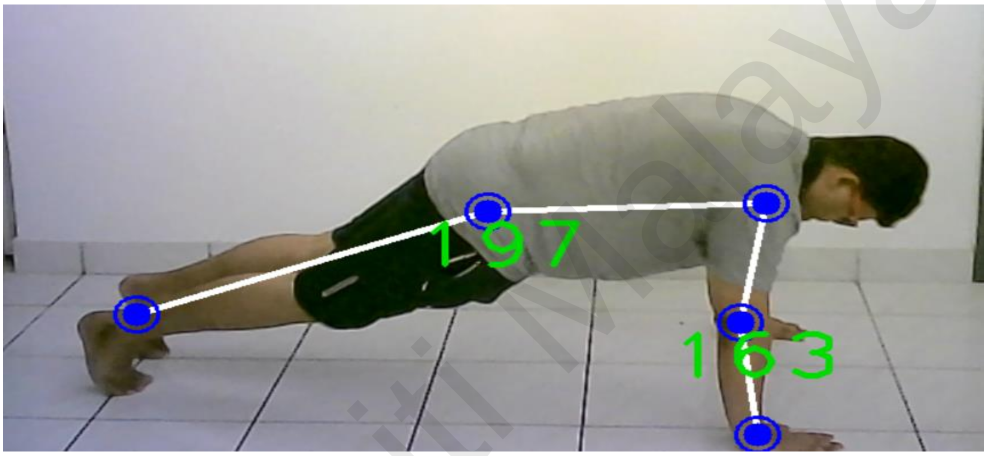

Figure 3.19: Node selection for Full Plank

A single angle calculation is used for a few exercises. The Yogic Squat exercise will have single angle and two distance calculation as shown in Figure 3.5. The few exercises like Push-ups, Semi Push-ups, Elbow plank, Full plank will have more than two angle calculations for analyzation. Table 3.1 shows the selection of nodes with the reference points and condition sets in accordance with the BlazePose Topology.

Table 3.1: Summation of selection of nodes and conditions

S.NO	Exercises	Node (Key Points)	Conditions
1.	Squat	Angle (23,25,29)	100<α<160
2.	Yogic Squat	Angle (28,26,23)	220<α<270
		Distance (26,23)	β<165
		Distance (7,14)	β<165
3.	Curls	Angle (11,13,15)	220<α<330
4.	Side Lounges	Angle (32,0,31)	345<α<310
5.	Left Side Leg Rise	Angle (24,23,29)	215<α<240
6.	Right Side Leg Rise	Angle (30,24,23)	105<α<130
7.	Left Fire Hydrants	Angle (23,25,27)	90<α<120
8.	Right Fire Hydrants	Angle (24,26,28)	250<α<220
9.	Step ups	Distance (29,30)	30<β<120
10.	Jack Knives	Angle (17,23,31)	180<α<345
11.	Knee Crunches	Angle (13,23,25)	285<α<315
12.	Push ups	Angle (16,12,30)	60<α<75
		Angle (12,14,16)	α<165 and α>60
		Angle (12,24,30)	α>165
13.	Semi Push ups	Angle (16,12,24)	80<α<95
		Angle (12,14,16)	α<165 and α>60
14.	Wall stand	Angle (24,25,27)	215<α<250
15.	Full Plank	Angle (12,14,16)	140<α<160
		Angle (28,24,12)	165<α<185
16.	Elbow Plank	Angle (14,12,24)	70<α<80
		Angle (12,24,28)	165<α<180

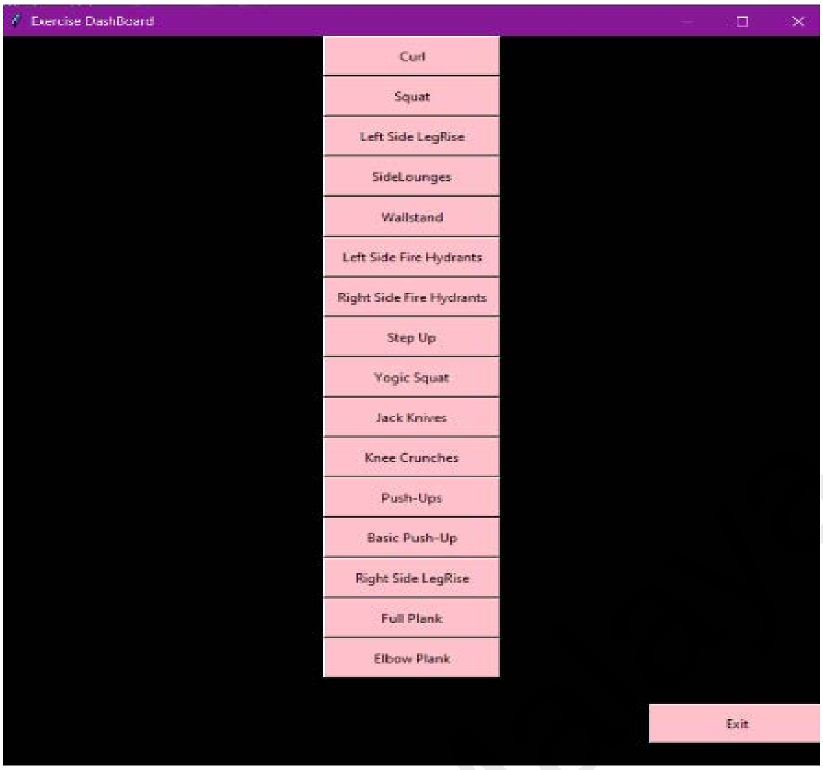

Figure 3.20: Exercise Dashboard

Figure 3.20 is the Exercise Dashboard created using the Python program. The user can select the list of exercise available from the dashboard, each option GUI will work as button function, the analyzation of the exercise will begin for the selection.

3.6 Summary

This chapter provides the brief methodology of this proposed work. It explained the architecture of the system, angle and distance calculation method, the threshold condition, selection of the nodes based on the exercise postures and explained the exercise analyzation methods.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Introduction

This chapter explains the results of exercise analyzation which is analyzed by the proposed system. The discussion will have briefing about the counting methodology, characteristic curves of the accuracy, predictions, and performance of the model in the user environment.

4.2 Output of the implemented system

The BlazePose model and methodologies proposed in this work are implemented using Python frameworks. The Exercise Dashboard was created using Tkinter GUI and results were displayed as Human Interactive model. The following Figures clearly shows the interactive system which display accuracy, counting methodology dynamically according to the changes in the human exercise postures.

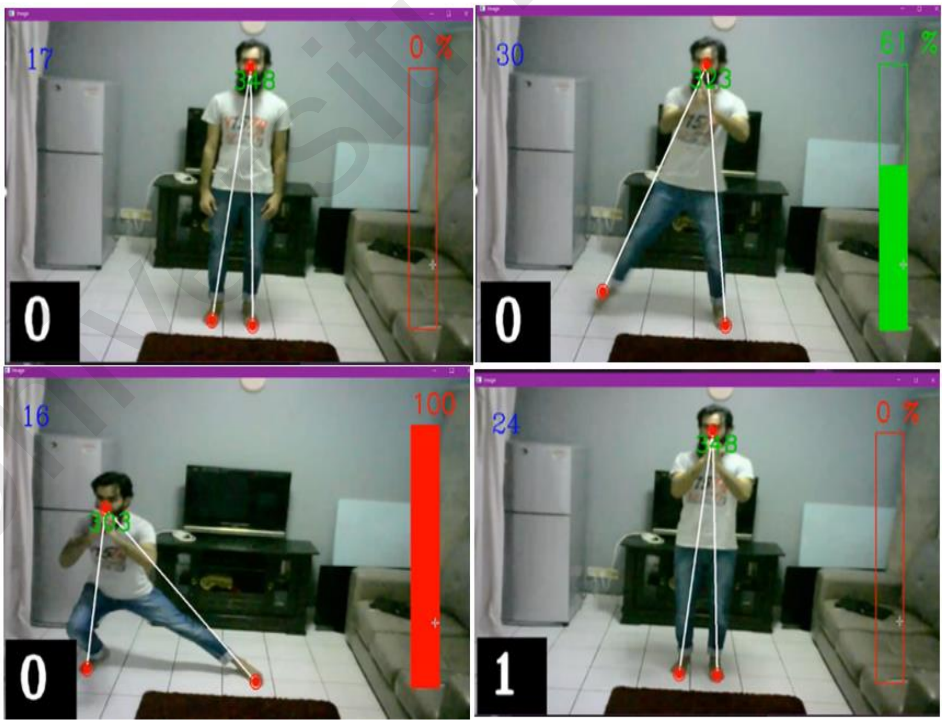

Figure 4.1: Execution of Side Lounges

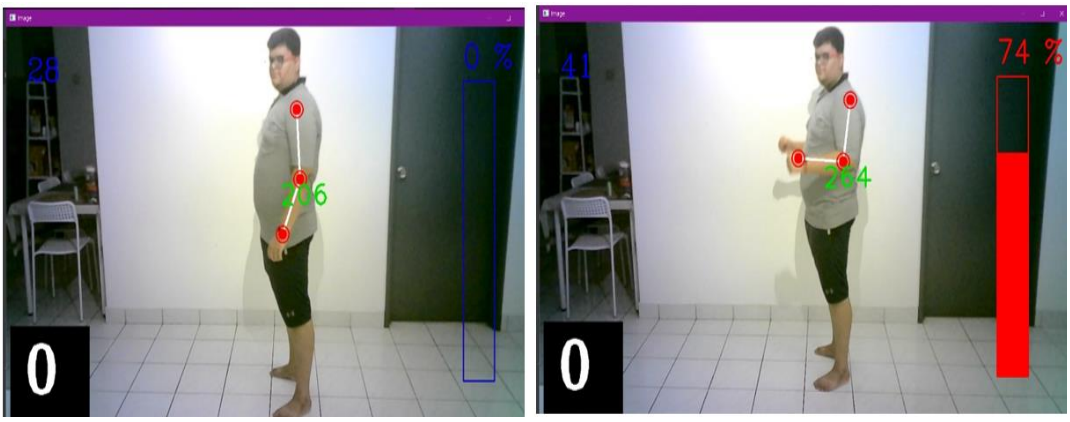

Figure 4.2: Execution of Curl

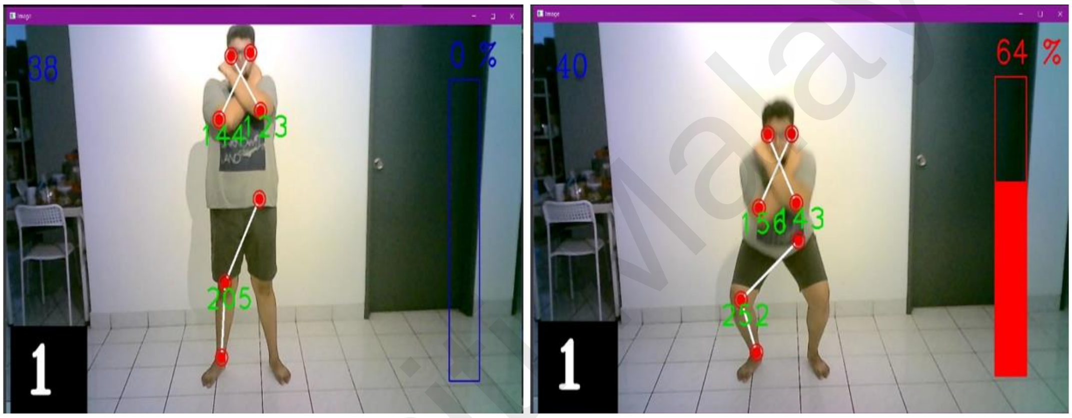

Figure 4.3: Execution of Yogic Squat

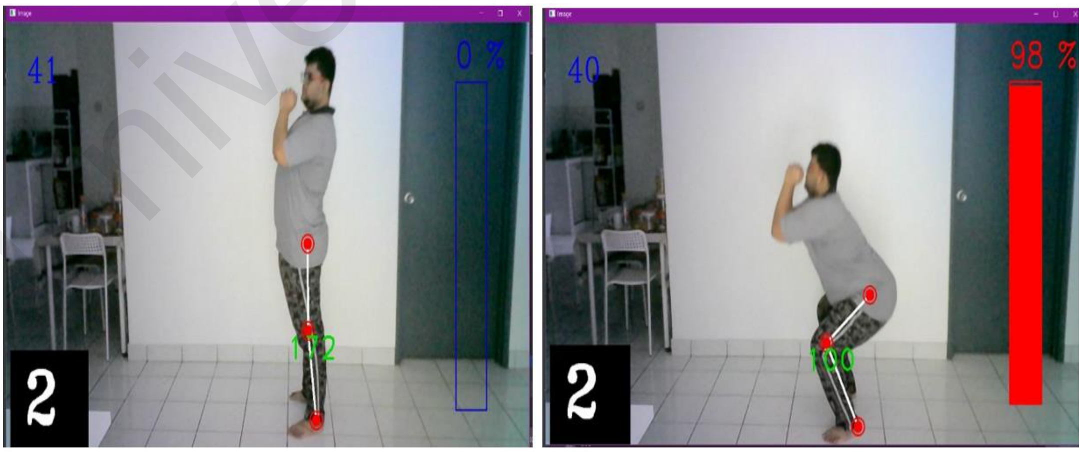

Figure 4.4: Execution of Squat

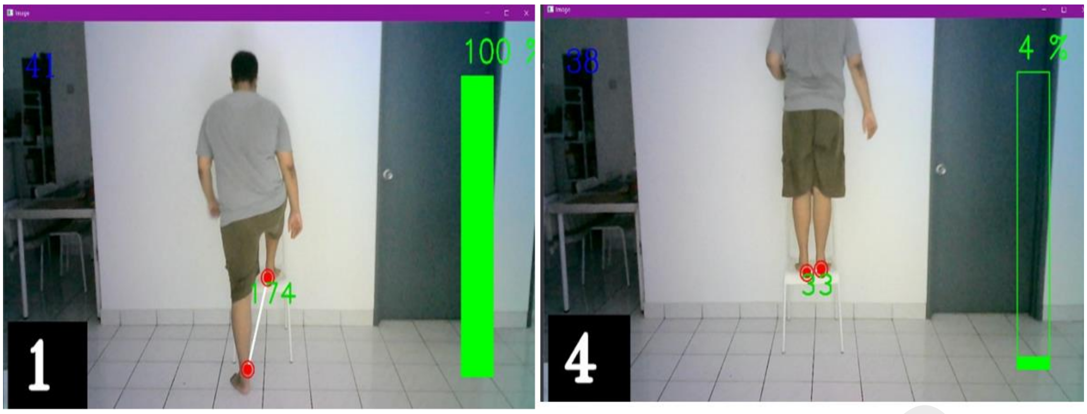

Figure 4.5: Execution of Step-up

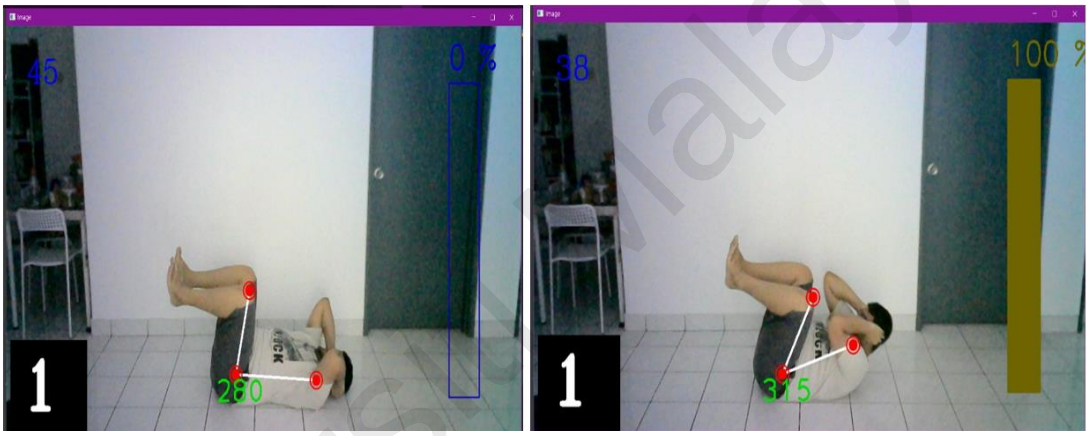

Figure 4.6: Execution of Knee Crunches

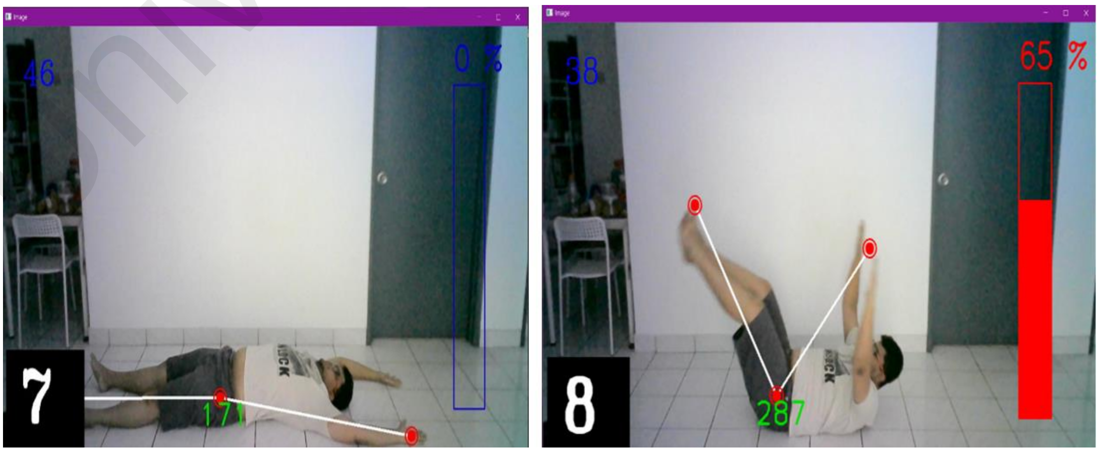

Figure 4.7: Execution of Jack Knives

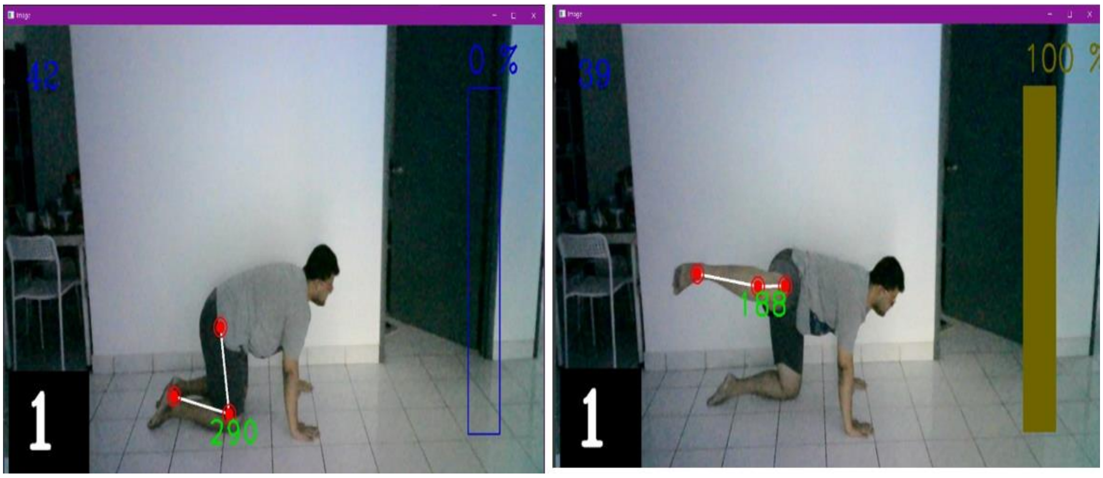

Figure 4.8: Execution of Right Fire Hydrants

Figure 4.9: Execution of Left Fire Hydrants

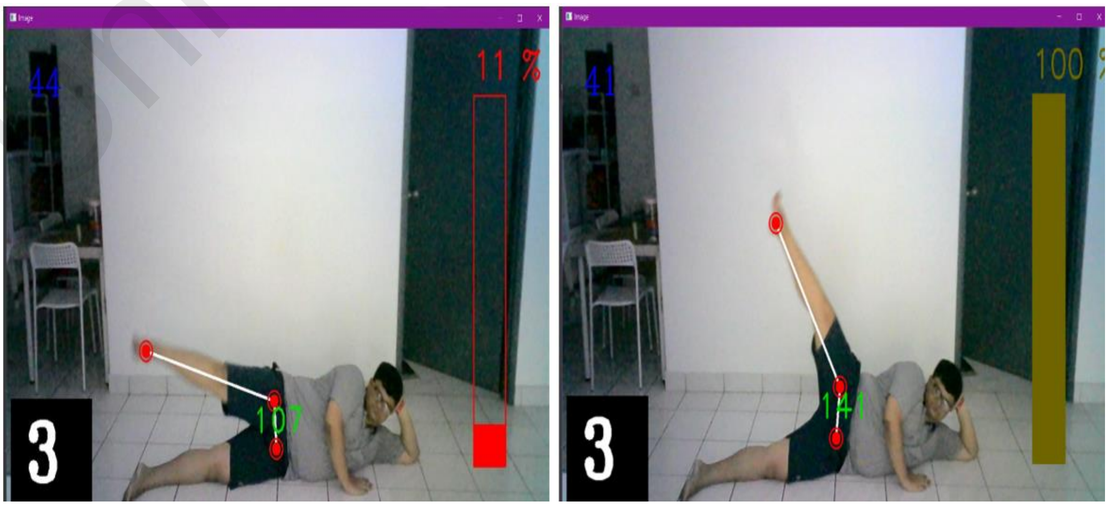

Figure 4.10: Execution of Right Leg rise

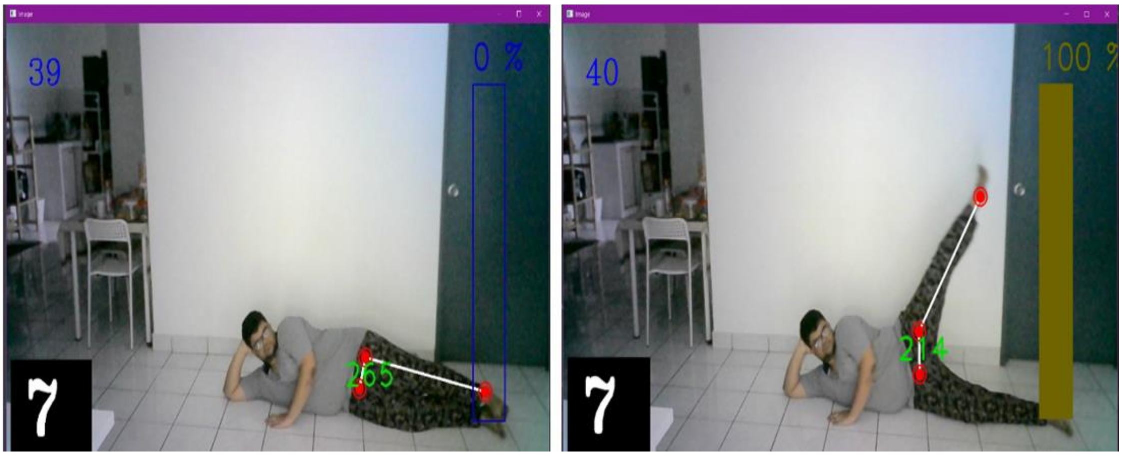

Figure 4.11: Execution of Left Leg rise

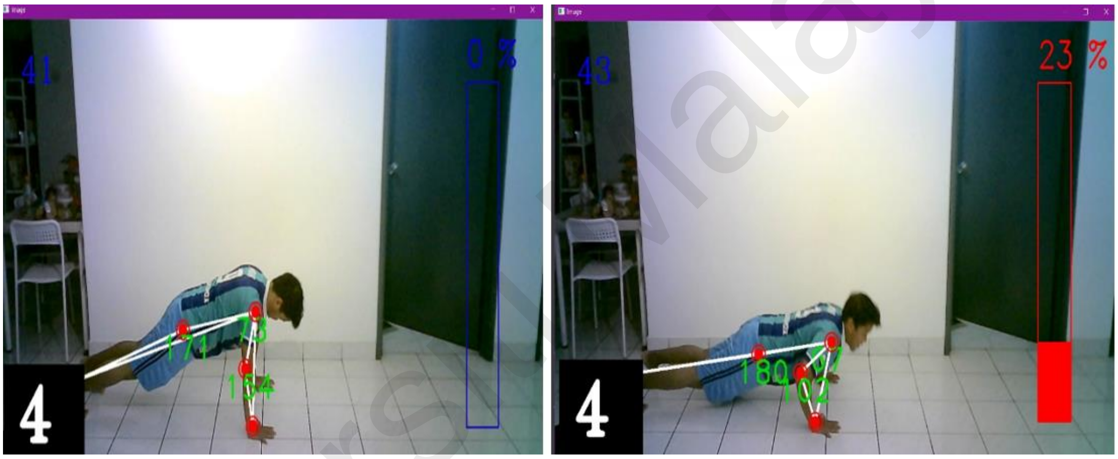

Figure 4.12: Execution of Push-ups

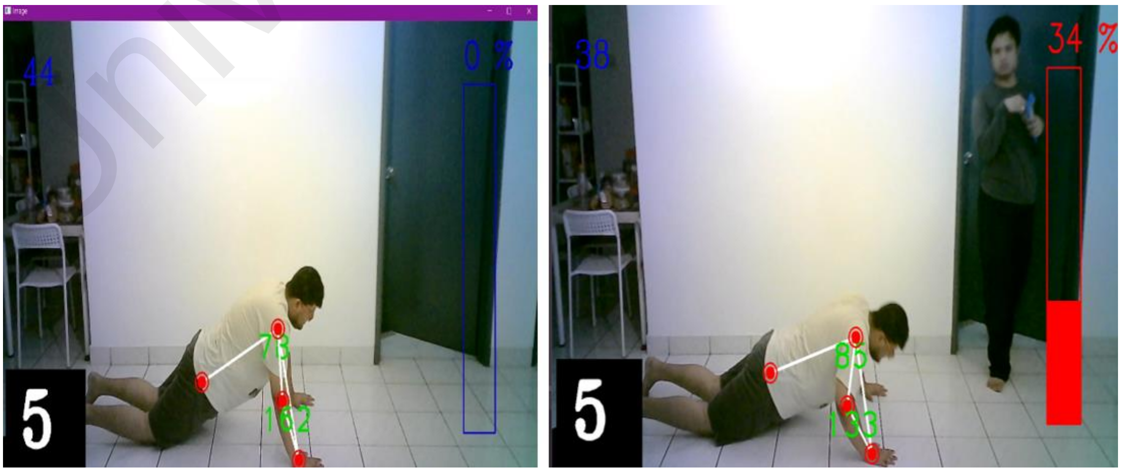

Figure 4.13: Execution of Semi Push-ups

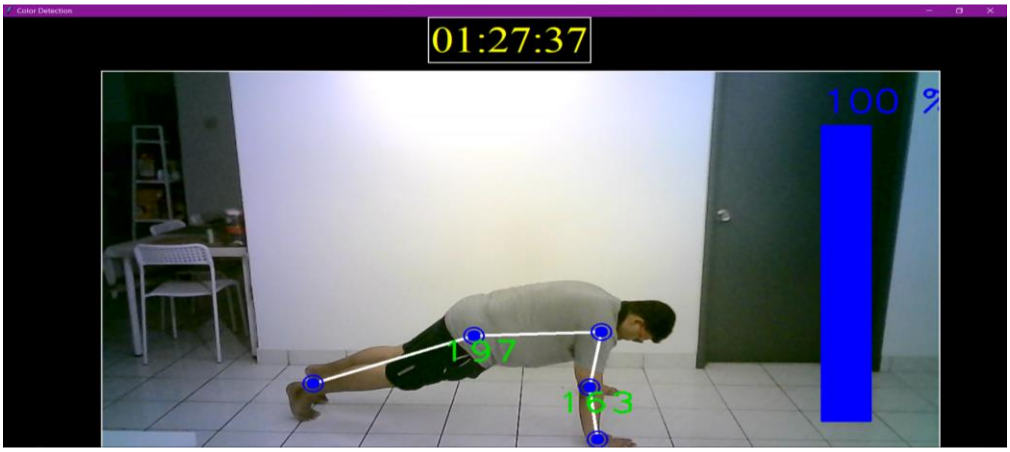

Figure 4.14: Execution of Full Plank

Figure 4.15: Execution of Elbow plank

Figure 4.16: Execution of Wall Stand

Table 4.1: Counting methods for exercises

S.NO	Exercises	Output (Counts or Timer)
1.	Squat	Count (increased by 1)
2.	Yogic Squat	Count (increased by 1)
3.	Curls	Count (increased by 1)
4.	Side Lounges	Count (increased by 1)
5.	Left Side Leg Rise	Count (increased by 1)
6.	Right Side Leg Rise	Count (increased by 1)
7.	Left Fire Hydrants	Count (increased by 1)
8.	Right Fire Hydrants	Count (increased by 1)
9.	Step ups	Count (increased by 1)
10.	Jack Knives	Count (increased by 1)
11.	Knee Crunches	Count (increased by 1)
12.	Push ups	Count (increased by 1)
13.	Semi Push ups	Count (increased by 1)
14.	Wall stand	Timer
15.	Full Plank	Timer
16.	Elbow Plank	Timer

The counting methodology for each exercise is tabulated in the Table 4.1. Implemented method was clearly explained in Figure 4.1 for the side lounges exercise, rest of the exercises except wall stand, full plank, elbow plank follows same counting system as shown in Figure 4.1, Figure 4.2, Figure 4.3, Figure 4.4, Figure 4.5, Figure 4.6, Figure 4.7, Figure 4.8, Figure 4.9, Figure 4.10, Figure 4.11, Figure 4.12, Figure 4.13. Meanwhile, Figure 4.14, Figure 4.15, Figure 4.16 shows the timer output method.

4.3 Robustness of the system

The implemented system was tested with the different users. The system can identify and analyze exercise for all age groups. The pre-processing technique like regularization is not used, because the nodal analysis of human pose is used to estimate the pose. The system mainly works on the data acquired by the camera, it works better under the better lighting environment and only one user can perform exercise to verify the results. The input video frames are resized to 1280x720 pixel size to clearly identify the nodal points. The Postures which are performed outside the Region of Interest cannot led exercise analyzation process due to missing of nodal points. The User can perform exercise within range of 3m to 5m distance away from the camera, exceeding the range could not give better results. The range is calculated based on the few trials, beyond the 5m distance away the user will not be in the Region of Interest of the camera, and the system could not identify nodal points and perform analyzation for the performed exercise.

4.4 Summary

This chapter, initially, explains the results as output of the exercises performed in user environments. chapter provides information on accuracy estimation based on the calculations and gives the comparison of the counting methods for exercises. At last, this chapter discusses the robustness of the implemented system.

CHAPTER 5: CONCLUSION AND FUTURE WORK

5.1 Conclusion

The identification and analyzation of exercise is achievable only with complex invasive system design. The few non-invasive methods are also proposed earlier this works are mostly computationally expensive. The human exercise pose should be analyzed with simple system, that should give better accuracy. The extraction of features is a crucial process for the better analyzation.

In this research project, the proposed system identifies and analyses the exercise postures non-invasively with simple design. At the same time, a total of 14 types of exercises are analyzed in most of the exercise environments. The system gives better output characteristics, the experiment adopted computer vision and deep learning model to accomplish the expected outcomes. We conducted intensive testing on different users to evaluate the performance of the proposed system. The model dynamically performs well and give better output.

5.2 Future work

The model performs well on the user environments, but still there are some limitations for the methods. The following steps can be the limitations which can be extended, for further research:

1.The exercise postures are analyzed in this project, based on the user's selection. The new design approach is needed to overcome this limitation. This is a complicated work that needs additional research, due to because of the mixture or similarity of the same exercise postures.

2.This project has completed an analysis for 14 exercises. However, there are lot more exercises are out there, which need experimentation of postures to analyze those posture patterns.

3.The proposed computer vision techniques failed to analyze some of the exercises like Jump Rope, Jump squat and etc. Therefore, further extension of works are needed to analyze these exercises.

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