

VIRTUAL SAFETY TRAINING SYSTEM BY USING MACHINE LEARNING

Submitted in partial fulfillment of the requirements for the award of Bachelor of
Technology degree in Biomedical engineering

by

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**DEPARTMENT OF BIOMEDICAL ENGINEERING
SCHOOL OF BIO AND CHEMICAL ENGINEERING**

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY

(DEEMED TO BE UNIVERSITY)

Accredited with Grade "A" by NAAC

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **S. Mercy (38240015)**, **Avigna Sai (38240006)** who carried out the project entitled "**Virtual Safety Training System using Machine Learning**" under our supervision from **September 2021 to March 2022**.

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DECLARATION

We **Mercy S (38240015)**, **Avigna Sai (38240006)** hereby declare that the Project Report entitled “**Virtual Safety Training System Using Machine Learning**” done by us under the guidance of Dr. **ANIMA NANDA**, Ph. D., FNRS, FAB, FIAS Department of Biomedical Engineering is submitted in partial fulfillment of the requirements for the award of Bachelor of Technology degree in Biomedical Engineering.

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ABSTRACT

Despite numerous devices targeted at fitness tracking, the strength training domain has often been overlooked and understudied. We propose a camera-based approach to track users' strength training workouts about their form and performance. We gather data from two sources for 5 exercises. We compute performance metrics such as range of motion, velocity, and duration from each repetition with median errors of less than 10%. The artificial intelligence camera records the data analyses of human pose points based on angle-wise movement in the body. These results demonstrate that a commercial off-the-shelf camera can detect and count repetition in user movements and compute rep-by-rep user performance. Many patients are unable to finalize the rehabilitation program because they consider the exercises to be difficult and repetitive. In addition to this, we measure heart rate, spo2, temperature, and humidity with help of hardware called Node MCU (MicroController Unit, ESP8266 Wi-Fi device with frequency -2.5GHz). In this system, the Heart Beat Rate, and SpO2 detector are used to measure SpO2, heartbeat rate, and temperature range. The SpO2 probe is placed on the person's finger and the other end with a microcontroller to calculate the number of pulses and the amount of the SpO2 present on their body. The measurement ranges of the SpO2, Heart Beat Rate, and Temperature are viewed via an online web page and the same is viewed by the doctor on the other end through the cloud. We analyze the recorded data to give suggestions about the user's progress which helps in setting a goal for the future.

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LIST OF ABBREVIATIONS

MCU	-	MICROCONTROLLER UNIT
ML	-	MACHINE LEARNING
RFA	-	RANDOM FOREST ALGORITHM
A. I	-	ARTIFICIAL INTELLIGENCE
PAFs	-	PART AFFINITY FIELDS
CPF	-	CASCADE PREDICTION FUSION
PGNN	-	POSE GRAPH NEURAL NETWORK
CFA	-	CASCADE FEATURE AGGREGATION
SPT	-	SINGLE-PERSON POSE TRACKING
VOT	-	VISUAL OBJECT TRACKING
MSPN	-	MIXED SUM-PRODUCT NETWORKS
FCNs	-	FULLY CONVOLUTIONAL NETWORKs
CPS	-	CYBER-PHYSICAL SYSTEM
ACL	-	ANTERIOR CRURIAE LIAGMENT
VR	-	VIRTUAL REALITY
XR	-	EXTENDED REALITY
DHM	-	DIGITAL HUMAN MODEL
CNN	-	CONVOLUTIONAL NEURAL NETWORK
DNN	-	DEEP NEURAL NETWORK
HRN	-	HIGHER HRNET
CV	-	COMPUTER VISION
IDE	-	INTEGRATED DEVELOPMENT ENVIRONMENT

VCSes	-	VERSION CONTROL SYSTEMS
HPE	-	HUMAN POSE ESTIMATION
RGB	-	RED GREEN BLUE
VR	-	VOLTAGE REGULATOR
PCB	-	PRINTED CIRCUIT BOARD
IC	-	INTEGRATED CIRCUIT
MOS	-	METAL OXIDE SEMICONDUCTOR
UART	-	UNIVERSAL ASYNCHRONOUS RECEIVER-TRANSMITTER
LED	-	LIGHT EMITTING DIODE
ADC	-	ANALOG TO DIGITAL CONVERTER
LCD	-	LIQUID CRYSTAL DISPLAY
BPM	-	BEATS PER MINUTE
DHT	-	DIGITAL TEMPERATURE AND HUMIDITY
IoT	-	INTERNET OF THINGS

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CHAPTER 1- INTRODUCTION

The project provides a solution to count repetitions of a physical exercise in real-time. The method uses pose estimation to track patients, recognize their performed exercises, count the repetitions, and analyze the performance of the repetitions. Open Pose is a real-time network that detects human poses and extracts their skeleton key points from an input video or an external camera. The open pose is widely used in software backgrounds like python and C++. A human pose skeleton represents a user's alignment in a certain structure. It's essentially a bunch of data points that can be combined to characterize a person's pose. Each skeletal data point is also known as a part, coordinate, or point. A limb or pair is a significant link between the two coordinates. A lot of approaches to human pose estimation have been proposed over the years, OpenPose provides a more efficient and robust approach that allows applying pose estimation to images (Zhe Cao et al., 2019). Machine learning (ML) is the study of computer algorithms that can learn and improve on their own given experience and data. Artificial intelligence is assumed to be an aspect of it. Machine learning algorithms develop a model based on training data and use this to make predictions or decisions without having to be explicitly programmed to do so. Techniques for machine learning are utilized in a wide range of applications, including medicine (Gesina Schwalbe et al., 2020). Supervised learning algorithms create a mathematical model of a set of data that includes both the inputs and the outputs that are sought. An algorithm that learns to complete a task increases one that increases the accuracy of its outputs or predictions over time. When the outputs are restricted to a relatively set of values, classification algorithms are used, and regression algorithms are used when the outputs can have any numerical value within a range. It helps us to make wise decisions based on our performance. Ranking, recommendation systems, visual identification tracking, face verification, and speaker verification are some of the uses. A random forest algorithm is a machine learning technique that's used to solve regression and classification problems. It exploits ensemble learning, a method for addressing complex problems by integrating many classifiers presented to the user in such a way that without the need for user interaction it determines the exercise for different users with the RFA (random forest algorithm), thereby finding the repetition of the exercises and

recording. The AI camera is used as an assistant to help the patient exercise independently. With the final data, we analyze and give the user suggestions on their progress and use it for future reference. We measure heart rate, spo2, temperature, and humidity with help of hardware called Node MCU (ESP8266 Wi-Fi device with frequency -2.5GHz). IoT is a connecting bridge between users and physicians to analyze their live performance across web pages. A precision of 95.3% and 99.4% is obtained for recognition of activity and repetition count, respectively. We introduce the comfort factor, which is the status of physical ease during training.

CHAPTER 2- LITERATURE SURVEY

1. Zhe Cao, Gines Hidalgo, Tomas Simon, Shih-En Wei, and Yaser Sheikh Open Pose: Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields: Real-time approach to detect the 2D pose of multiple people in an image. The proposed method uses a nonparametric representation; refer to as Part Affinity Fields (PAFs), to learn to associate body parts with individuals in the image. The accuracy and real-time performance of this bottom-up technology are exceptional. This work has culminated in the release of Open Pose, the first open-source real-time system for multi-person 2D pose detection, including body, foot, hand, and facial key points.

2. Hong Zhang, Hao Ouyang, Shu Liu, Xiaojuan Qi, Xiaoyong Shen, Ruigang Yang, Jiaya Jia. Human Pose Estimation with Spatial Contextual Information: The importance of spatial contextual information in human pose estimation, pose networks are trained in a multi-stage manner and produce several auxiliary predictions for deep supervision. Two conceptually simple and yet computationally efficient modules, namely Cascade Prediction Fusion (CPF) and Pose Graph Neural Network (PGNN), to exploit underlying contextual information. CPF makes use of rich contextual information encoded in the auxiliary score maps to produce enhanced prediction, whereas PGNN provides a scheme to refine prediction. They are also generally for most existing pose estimation networks to boost performance.

3. Zhihui Su, Ming Ye, Guohui Zhang, Lei Dai, Jianda Sheng Cascade Feature Aggregation for Human Pose Estimation: Deep convolutional neural networks are an effective way to improve the accuracy of human pose estimation. Cascade Feature Aggregation (CFA) is a method for robust human posture prediction that cascades many hourglass networks. The extensive experiments on MPII datasets and LIP datasets demonstrate the proposed CFA outperforms the state-of-the-art and achieves the best performance on the state-of-the-art benchmark MPII.

4. Ke Sun, Bin Xiao, Dong Liu, Jingdong Wang Deep High-Resolution Representation Learning for Human Pose Estimation: The human pose estimation problem with a focus on learning reliable high-resolution presentations. Multi-scale fusions in which each of the high-to-low resolution representations repeatedly receives information from other parallel representations, resulting in rich high-resolution representations. As a result of this more accurate and spatially more precise.

5. Guanghai Ning, Heng Huang. LightTrack: A Generic Framework for Online Top-Down Human Pose Tracking: A modular single-person pose estimation module combines Single-person Pose Tracking (SPT) and Visual Object Tracking (VOT) into a single unified operational entity. A novel effective light-weight framework, called Light Track, for online human pose tracking. The framework is designed to be generic for top-down pose tracking and is faster than existing online and offline methods. This method outperforms other online methods while maintaining a much higher frame rate, and is very competitive with offline state-of-the-art.

6. Ongdong Yu, Kai Su, Changhu Wang Towards Good Practices for Multi-Person Pose Estimation: The MSPN and Pose Fix Networks empirically evaluate their impact on model performance through ablation studies. Multi-person pose estimation using the top-down pipeline. The MSPN network adopts the ResNet-50 as the backbone of the encoder and decoder, a new backbone, named Refine-50, which can well handle the scale variant cases. By taking all the refinements, the COCO test-dev dataset and the COCO test-challenge dataset with greater accuracy.

7. Adrian Bulat, Jean Kossaifi, Georgios Tzimiropoulos, Maja Pantic Toward fast and accurate human pose estimation via soft-gated skip connections: Fully Convolutional Networks (FCNs), residual connections within FCNs have proved to be quintessential for achieving high accuracy, and efficiency. Gated skip connections with per-channel learnable parameters to control the data flow for each channel, a hybrid network that combines the Hourglass and U-Net architectures which minimizes the number of identity connections within the network. Achieves state-of-the-art results on the MPII and LSP datasets, shows no decrease in performance when compared to the original Hourglass network.

8. Ana Pereira and Carsten Thomas Challenges of Machine Learning Applied to Safety-Critical Cyber-Physical Systems: Machine Learning (ML) is increasingly being used to control safety-critical Cyber-Physical Systems (CPS) in areas where traditional control methodologies are difficult to grasp. ML-based control systems and their certification, identified hazards are illustrated and explained using a real-world application. Identifying the issues that can arise throughout the design and development of a system with an integrated ML algorithm, as well and which safety hazards can be created during each phase of the ML lifecycle's specific activities.

9. Nathaniel Blanchard, Kyle Skinner, Aden Kemp, Walter J. Scheirer, Patrick J. Flynn. "Keep me in, Coach!": A Computer Vision Perspective on Assessing ACL Injury Risk in Female Athletes: Foundational dataset of multi-video recordings of scripted athletic movements to enable the development of computer vision that evaluate and identifies lower-body injury risk and focuses on the female athletes, who are at risk of anterior cruciate ligament (ACL) injury. The data are obtained from the dataset centers on the type of movement replicated with ease by non-experts. Data from the camera was manually aligned and extract knee information from athletes. Athletes or researchers will be able to easily replicate the set and assemble a compatible and complementary dataset to propel the development and assessment of injury propensity models.

10. Bruno Artacho and Andreas Savakis OmniPose: A Multi-Scale Framework for Multi-Person Pose Estimation: Omni Pose, a single-passed end-to-end trainable framework for multi-person pose estimation. Omni Pose incorporates contextual information across scales and joint localization with Gaussian heat map modulation at the multi-scale feature extractor to estimate human pose with state-of-the-art accuracy. Multiple datasets demonstrate that Omni Pose, with an improved HRNet backbone and waterfall module, is a robust and efficient architecture for multi-person pose estimation that achieves state-of-the-art results.

11. Bruno Artacho and Andreas Savakis UniPose: Unified Human Pose Estimation in Single Images and Videos: UniPose is a unified framework for estimating human pose based on Atrous Spatial Pooling's "Waterfall" design. UniPose-LSTM achieves state-of-the-art performance for temporal posture estimation in the video when used for multi-frame processing. UniPose is a robust and efficient architecture for posture estimation that obtains state-of-the-art results in single-person pose identification for both single photos and recordings, it was achieved with the help of ResNet backbone and Waterfall module.

12. Bowen Cheng, Bin Xiao, Jingdong Wang, Honghui Shi, Thomas S. Huang, Lei Zhang HigherHRNet: Scale-Aware Representation Learning for Bottom-Up Human Pose Estimation: HigherHRNet: a novel bottom-up human pose estimation method for learning scale-aware representations using a high-resolution feature pyramid, equipped with multi-resolution supervision for training and aggregation for inference. The feature pyramid in HigherHRNet consists of feature map outputs from HRNet and upsampled higher-resolution outputs through a transposed convolution. An efficient high-resolution feature pyramid based on HRNet and train it with multi-resolution supervision. HigherHRNet outperforms all existing bottom-up methods by a large margin on the challenging COCO dataset, especially for small persons.

13. Michail Pavlou, Dimitrios Laskos, Evangelia I. Zacharaki, Konstantinos Risvas, and Konstantinos Moustakas an XR training system for interactive simulation and ergonomics assessment: virtual reality (VR) and Extended reality (XR). The XR tutorial creation module (automatic recognition), the XR tutorial execution module (for the delivery), the digital human model (DHM) (simulation module for creation and demonstration) the biophysics assessment module (for ergonomics analysis). Three-dimensional reconstruction and aligned projection of the objects situated in the real scene facilitated the imposition of inherent physical constraints, thereby allowing to seamlessly blend the virtual with the real world without losing the sense of presence.

14. Wen-Nung Lie, Guan-Han Lin, Lung-Sheng Shih, Yuling Hsu, Thang Huu Nguyen, Quynh Nguyen Quang Nhu. Fully Convolutional Network for 3D Human Skeleton Estimation from a Single View for Action Analysis: Fully Convolutional Networks (FCNs). 3D Human Anchor Pose (i.e., the most similar and frequently occurring pose in the dataset) 3D anchor pose to its final state (parameters). According to experiments, two-stage FCNs are capable of achieving an MPJPE (Mean per joint position error) when a 2D ground truth pose is used as the input. This can be improved if a 17-joints human skeleton model is adopted and re-trained based on the dataset H36M (terms of FOV, focal length, or human distance).

15. Tommaso Dreossi, Alexandre Donzé, Sanjit A. Seshia Compositional Falsification of Cyber-Physical Systems with Machine Learning Components: Cyber-physical systems (CPS), machine learning (ML) components. A compositional falsification framework where a temporal logic falsifier and a machine learning analyzer cooperate to find falsifying executions of the considered model. The efficacy of the technique is shown in an automatic emergency braking system model with a perception component based on deep neural networks.

16. Feng Zhang, Xiatian Zhu, Hanbin Dai, Mao Ye, Ce Zhu Distribution-Aware Coordinate Representation for Human Pose Estimation: The aim is to detect the spatial location with help of a convolution neural network(CNN). The design limitations of the standard coordinate decoding method, encoding by generating unbiased/accurate heatmaps. A novel Distribution-Aware Coordinate Representation of Keypoints (DARK) method. It shows that DARK yields the best results on two common benchmarks, MPII and COCO.

CHAPTER 3 AIM AND OBJECTIVE

3.1 AIM:

Our goal is to detect the repetitions in a workout (physical) without requiring user intervention or any training data from the user. Unlike many existing systems, our proposed system is scalable, low-cost, and widely accessible.

3.2 OBJECTIVE:

- To the patients who can't come to the hospital
- To patients in absence of a physiotherapist
- To highly recommended for the high accuracy
- To patients helps in fast recovery
- To the teaching and verify the proper form and independent journey in training

CHAPTER 4 MATERIALS AND METHODOLOGY

4.1 EXISTING METHOD:

TECHNIQUE: Machine learning, Deep neural network(DNN), Convolution neural network(CNN), Fully Convolution Network(FCN), Cyber-Physical System(CPS), Virtual reality(VR), Extended Reality(ER), Higher HRNet (HRN), Single-Person Pose Tracking(SPT).

SYSTEM APPROACHES Bottom-up, Top-down.

METHOD: Part Affinity field(PAF)-Study of body movements individually, Cascade prediction fusion and pose graph neural network- Contextual information, Encoding, decoding, and, processing the image, ResNet50- Backbone of encoder and decoder, Machine learning(ML)- Act as human and provide solutions, Cascade feature aggregation(CFA), Robust human pose estimation, Movements are captured and processed with the help of dataset (COCO, MPII, LSP, HRN).

RESULT: An efficient output is obtained f with high accuracy and spatially more precise from a given method

DISADVANTAGE: It is not accessible to everyone. They follow only Key points and don't measure the angle between the points/joints.

4.2 PROPOSED METHOD:

TECHNIQUE: Machine learning, Random Forest Algorithm (supervised ML)

METHOD: Mediapipe is used for image analyses, detection, and recognition of the exercise. It also provides a solution for computer vision(CV) tasks. The version of Mediapipe is 0.8.6.2.

SYSTEM APPROACH: Top to Bottom.

The people exercise regularly, every week. But most of us don't follow a structured fitness plan, which can help the sufficiently achieve our goals. Monitoring the heart rate allows for measuring the improvements in their level of fitness. During exercise, more oxygen is required by the muscles and it is monitored with help of MAX3100, Heart rate sensors. There is a range of exercise intensities that is described as safe and effective for regulating cardiovascular benefits. When people start the exercise, the system can automatically interact with the user virtually and calculate the efficiency and calorie burn, and measure oxygen and heartbeat with a wearable device on the body. As an activity of recognition and repetition count is calculated in real-time, the raw signal is processed dynamically. The wavelet is scaled along the time axis to provide the frequency bands of interest by convolving it with the raw signal at a particular moment. It involves a technical algorithm random forest algorithm (RFA) detecting the quality of a user's predicted pose for a given exercise. We approach this using heuristic-based and machine learning models, using the poses and instruction of personal trainers and other qualified professionals as the ground truth for proper form. Accuracy of 95.3% and 99.4% is achieved for activity recognition and repetition count respectively. We introduce the Comfort factor, which is the state of physical ease during the workout.

ADVANTAGES:

1. Easy to use for the patients.
2. It is effortless to access with a time-saving process.
3. It is low cost and affordable.

4.3 SOFTWARE SYSTEM:

4.3.1 Pycharm:

Pycharm is a computer programming integrated development environment (IDE) that concentrates on the Python programming language. It features code analysis, a graphical debugger, an integrated unit tester, VCS integration, and Django and Anaconda support both web development and data science, accordingly. Pycharm is cross-platform, with Windows, macOS, and Linux versions. The use of pycharm here is enhanced with the coding of matrix and distances between two pose points. The supporting software that is used to build the GUI is Pyqt Software.

4.3.2 Machine Learning:

Machine learning (ML) is a subset of artificial intelligence (AI) that allows software applications to enhance their predictive performance without being explicitly designed to do so.

Machine learning classification is of three types:

- Supervised machine learning.
- Unsupervised machine learning.
- Reinforcement.

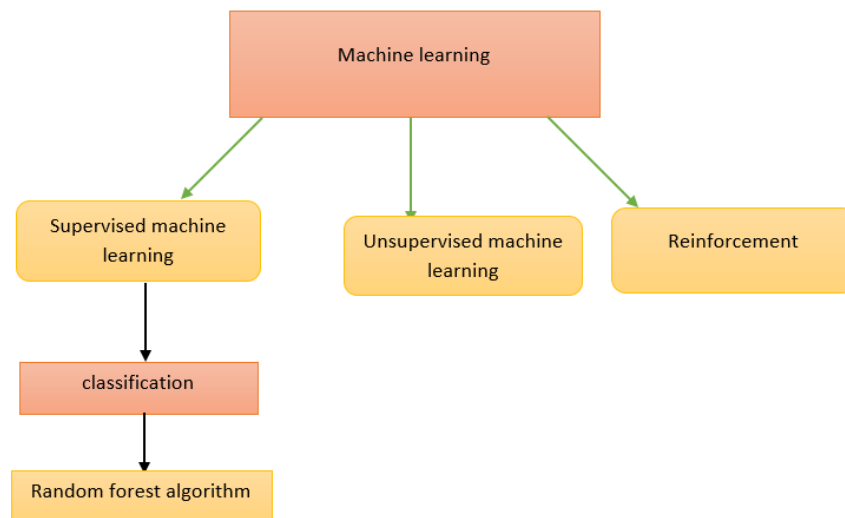


Fig: 4.1 Machine Learning Types.

4.3.3 Random Forest Algorithm:

Random forest is an extensively used supervised machine learning technique for classification and regression tasks. It uses the majority vote for classification and the average for regression to build decision trees from various samples. Bagging or bootstrap aggregation is often used to train the random forest algorithm. Bagging is a meta-algorithm that enhances the accuracy of machine learning methods by gathering them together. Bagging randomly selects samples of data from the entire set. As an outcome, each model is created using row sampling to replace the samples (Bootstrap Samples) provided by the Original Data.

Row sampling with replacement is referred known as the "bootstrap" step. Every model is now trained independently, and also the results are generated. After compiling the data of all models, the overall result is based on majority voting. Aggregation is the process of gathering all of the data and producing a result based on a majority vote. Using a random forest technique, the shortcomings of a decision tree algorithm are avoided. It reduces dataset overfitting and improves precision. It generates forecasts without requiring a large number of package configurations.

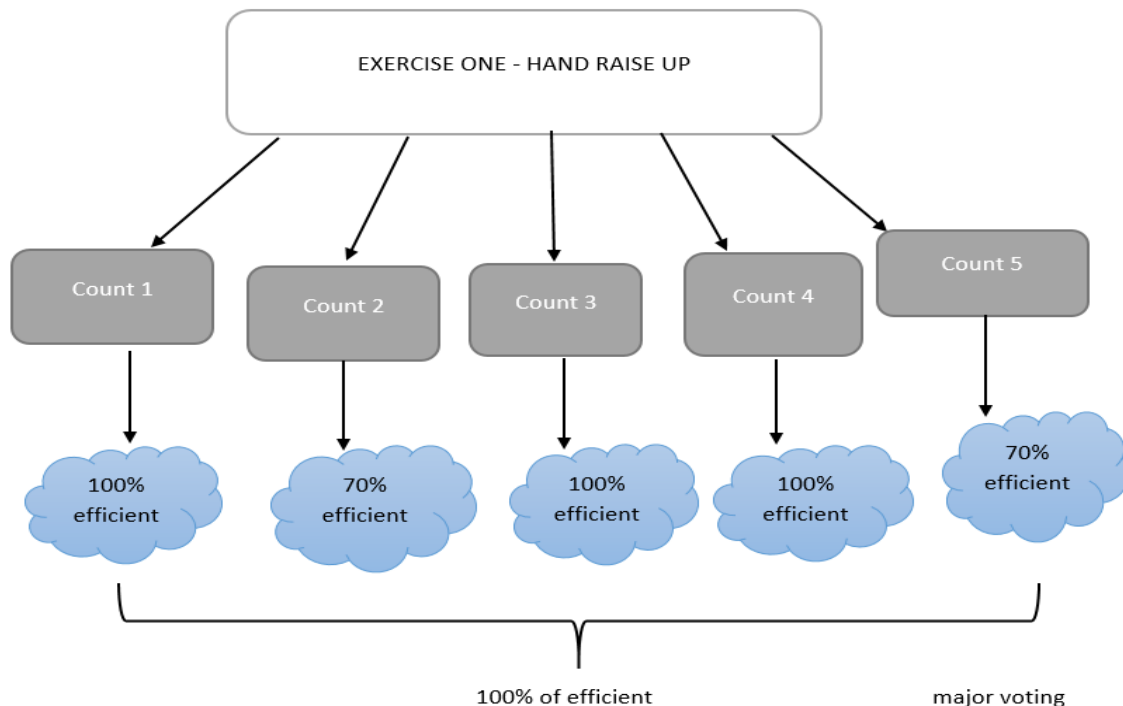


Fig: 4.2 Bagging Random Forest Algorithm

The above snapshot (fig:4.2) explains the bagging random forest algorithm. Here exercise one is repeated five times and the outcome is taken as the performance of efficiency during the exercise. The final output is based on majority voting after combining the results of the exercise.

4.3.4 Open Pose Human Estimation:

Pose estimation is a computer vision problem that is typically solved via deep learning. It is one of the interesting areas of research that has gained a lot of traction because of its usefulness and versatility, and its applications in a wide range of fields including gaming, healthcare, Augmented Reality, and sports. Human Pose Estimation (HPE) is a method of recognizing and classifying the human body's joints. It's essentially a way of capturing a set of coordinates for each joint (arm, head, torso, and so on) that may be used to describe a person's posture. A pair is a relationship between these two places. Since the connection created between them must be meaningful, not all points can form a pair. Open cv is a machine learning package that is used for capturing video and adding logic to verify their angles.

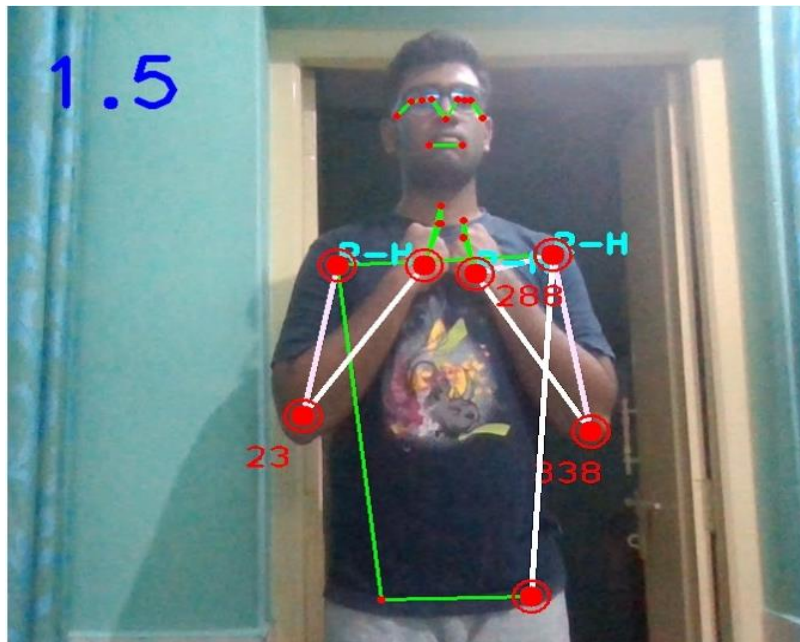


Fig:4.3 Schematic Representation of open pose

4.4 BLOCK DIAGRAM FOR SOFTWARE:

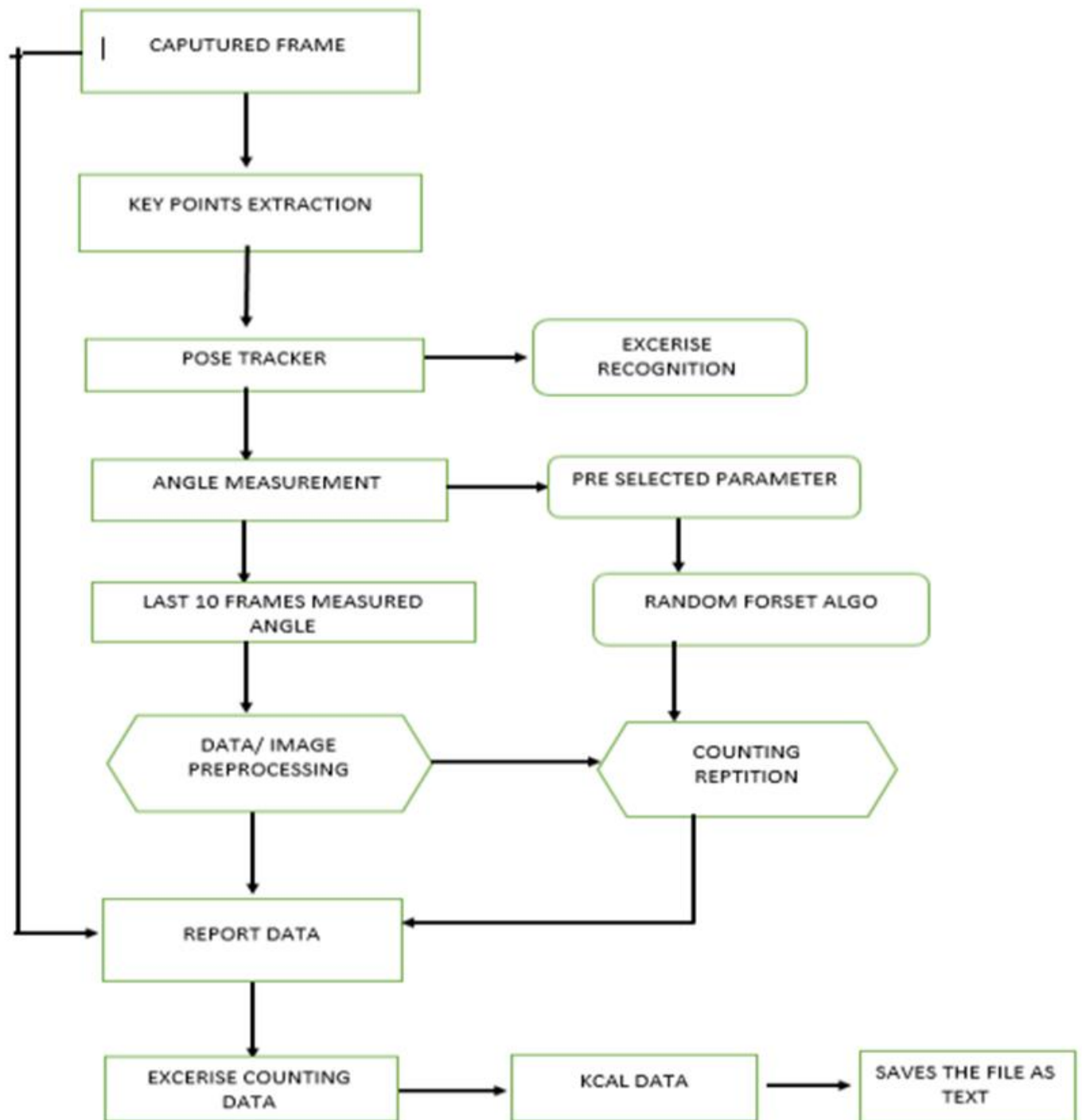


Fig:4.4 Schematic Representation of software execution

The above picture (fig:4.3) explains captures the frame and image are acquired, from this the key points are extracted from 0 to 7 points from our body. After determining the exercise, we are using a pose tracker to calculate the pose like 0 to 1, 1 to 2, 2 to 3, etc. up to 32, and exercise is recognized. Then the angle is measured from the pre-selected parameters.

For example: If we are doing right-hand rehabilitation, we are selecting the right-hand side as per the selected parameter. So the last 10 frames measured angle i.e. 1 full completion of the exercise, each frame is 0.5fps (frames per second). Then we are undergoing a random forest algorithm, which gives information based on the feedback, it comes under supervised machine learning. After that, the data is processed. i.e. when the input image and data angle match, it starts the counting process, and after completion, the data is reported. The exercise counting data & calorie data saves as text.

4.4.1 Key Points:

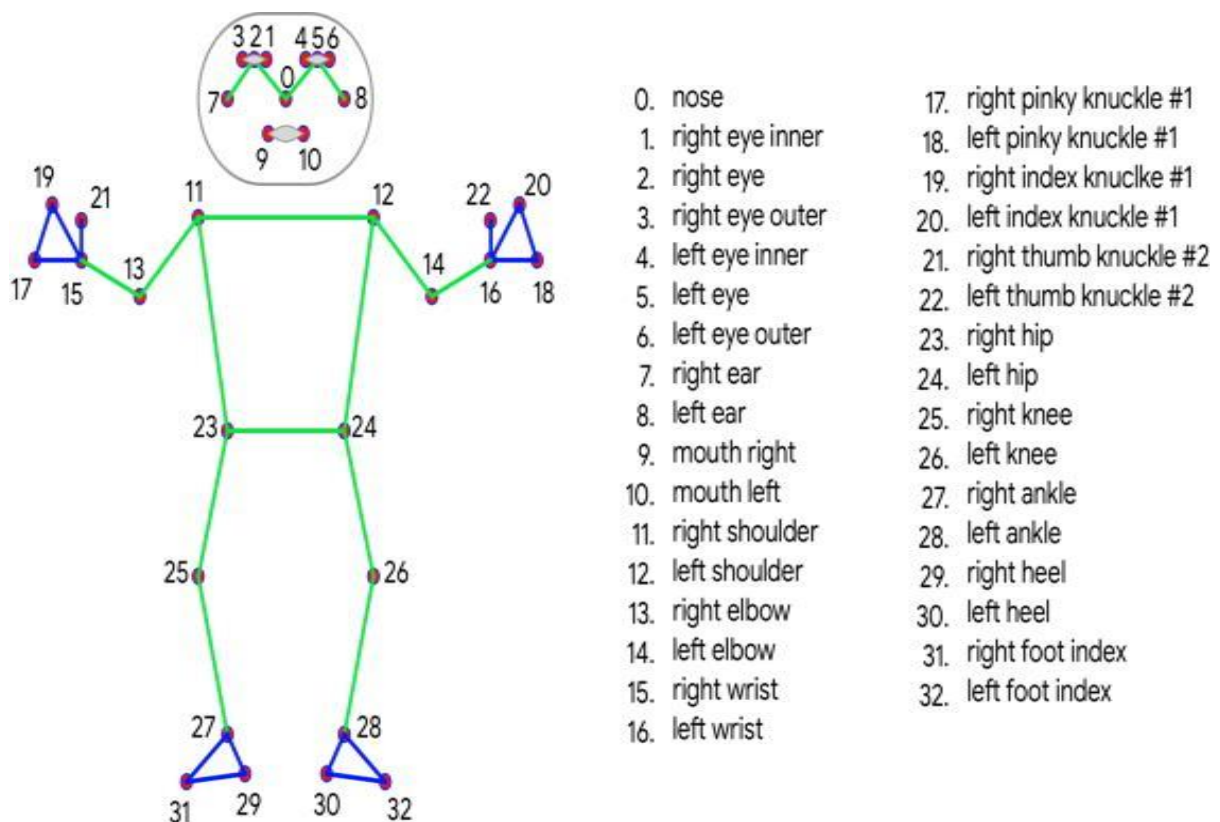


Fig: 4.5 Schematic representation of 32 Keypoints

In the world of computer vision, human pose estimation is an important study subject. It is concerned with determining the unique points on the human body, also known as Keypoints. In our research, we used a skeleton-based model with 32 essential points. Using our BlazePose research, which also powers the ML Kit Pose Detection API, Mediapipe Pose is an ML solution to enhance body pose tracking, insinuating 33 3D landmarks, and background segmentation mask on the complete body from RGB video frames. The use of media pipe in our work is to image analyses, detection, and recognition of the exercise. It also provides a solution for computer vision(CV) tasks.

4.5 HARDWARE COMPONENTS:

4.5.1 Power Supply:

The power source is a term that refers to the electrical component's source. Most circuits require a DC power supply. Here we use a 9-12 power supply.

Specification:

- Input; 90-270v -50/60Hz 0.5A
- Output: +/- 12 $\approx$ 1.0A

4.5.2 Voltage Regulator:

A voltage regulator is a device that generates and maintains a constant output voltage regardless of input voltage or load conditions. The voltages from a power source are kept within a range that is compatible with the other electrical components by voltage regulators (VRs). The voltage regulator IC 7805 is a member of the 7805 series of voltage regulator ICs. It is a fixed linear voltage regulator. The 05 present in 7805 represents the value of the fixed output voltage that the particular IC provides. For 7805 IC, it is +5V DC regulated power supply. This voltage regulator can accept an input voltage of up to 35V, and it can output a constant 5V for any input voltage less than or equal to 35V, which is the threshold limit.

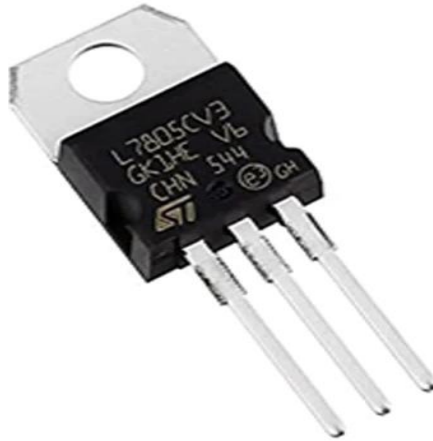


Fig: 4.6 LM7805

4.5.3 ESP8266 Microcontroller:

A microcontroller (MCU for microcontroller unit) is a mini-computer that is constructed from a single MOS integrated circuit (IC) chip. A microcontroller contains one or more CPUs (processor cores) with memory and programmable input/output peripherals. The ESP8266 Wi-Fi Module is a self-contained system on a chip with an integrated microcontroller that can connect to your Wi-Fi network using this Internet protocol stack. The ESP8266 might also host an application or offload full Wi-Fi networking capabilities to another processor. Because of its high level of on-chip integration, it only requires a small amount of external circuitry, including the front-end module, which is designed to fit on a small PCB. The ESP8266 Wi-Fi Module Adaptor comes with an onboard logic level converter and 3.3V low drop-out regulator for easy interfacing to controller boards.

Specification:

- Digital I/O pins- 11 pins, one pin is an analog pin.
- GPIO pins- 17 pins.
- Pulse Width Modulation- 4pins.
- UART- 2 pairs for UART (UART0 &UART1).
- RAM- 128Kb of RAM.
- Memory- 4Mb of flash memory.
- Clock Speed- 160MHz (80-160).
- Operating Voltage- 3.3V

- Input Voltage- 4.5-10V
- Current- 80mA.
- Wi-Fi Built-In- 802.11b/g/n.

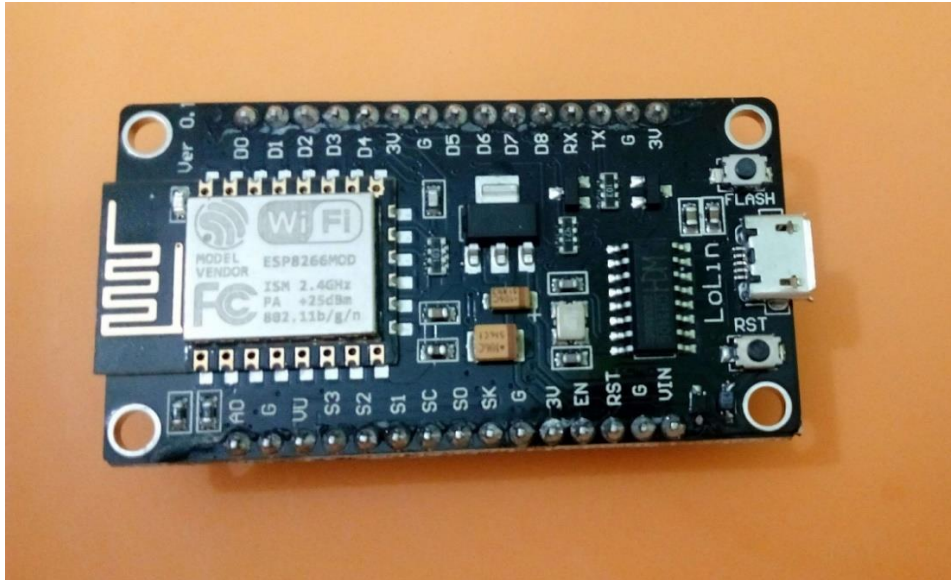


Fig: 4.7 ESP8266 Wi-Fi device

4.5.4 DHT11 Sensor:

DHT11 Temperature and Humidity Sensor features a calibrated digital signal output with the temperature and humidity sensor complex. Its technology provides a high level of dependability and long-term stability. It is the as excellent quality, has fast response, anti-interference ability, and high-cost performance. The product has 4-pin in which we use three pins (input, GND, output).

Specifications:

- Supply Voltage: +5 V
- Temperature range: 0-50 °C error of ± 2 °C
- Humidity: 20-90% RH $\pm 5\%$ RH error
- Interface: Digital

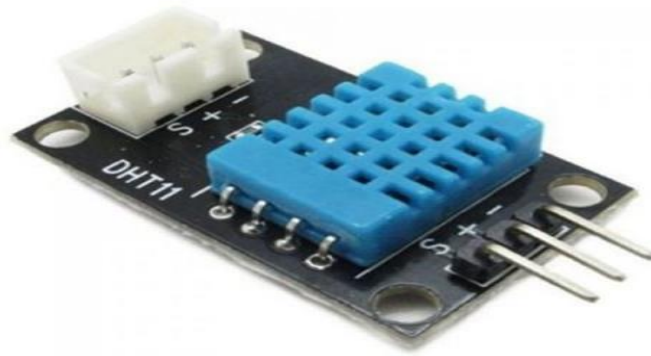


Fig: 4.8 DHT11 Sensor

Formula for converting from Celsius to Fahrenheit:

1. $^{\circ}\text{C} = 5/9 (^{\circ}\text{F} - 32^{\circ})$
2. $^{\circ}\text{F} = ^{\circ}\text{C} * 9/5 + 32.$

4.5.5 MAX3100:

The MAX30100 sensor combines pulse oximetry and a heart rate monitor into the same device. It detects pulse oximetry and heart rate signals using two LEDs, a photodetector, improved optics, and low-noise analog signal processing. The MAX30100 utilizes 1.8V and 3.3V power supplies, and it may be turned down by software with very little standby current, allowing the power supply to be connected at all times. The use of ADC is to convert body analog signals into digital signals. In addition to this, we added an I2C heart rate sensor to measure the heart rate. The Max sensor has 4pins.

Specification:

- Power supply voltage- 1.8-2.0V
- Led supply voltage – 3.1-5V

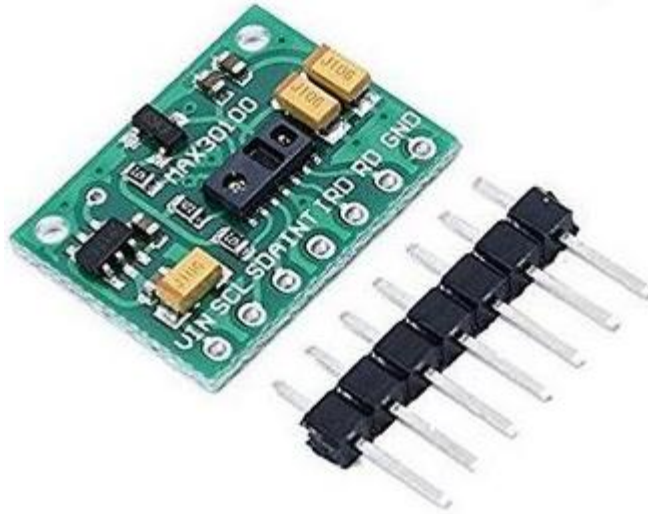


Fig:4.9 MAX3100 Sensor

4.5.6 LCD (LIQUID CRYSTAL DISPLAY):

A liquid-crystal display (LCD) is a flat-panel display or some other electronically controlled optical device that employs liquid crystals with polarizers to manipulate light. Instead of emitting light directly, liquid crystals use a backlight or reflector to create color or monochrome pictures. It uses a Hitachi HD44780 microcontroller to display messages in two lines of 16 characters each (16*2). Ground, VCC, VO, Register Select, Read/Write, Enable, Data Bits (0-7), LED positive, and LED negative pins are among the 16 pins.

Specification:

- Operating Voltage- 4.7-5.3V
- Display Size- 72x25mm.
- Operating Current- 1mA without backlight.
- PCB Size of the module- 80L x 36W x 10H mm.
- HD47780 Controller.
- LED color for backlight is GREEN/BLUE.
- Number of Columns & Rows- 16x2.
- Number of LCD pin- 16 and its characters is 32.
- It works in 4-bit and 8-bit modes.
- Pixel Box of each character is 5x8 pixel.

- Font size of the character is 0.125 width x 0.200 height.

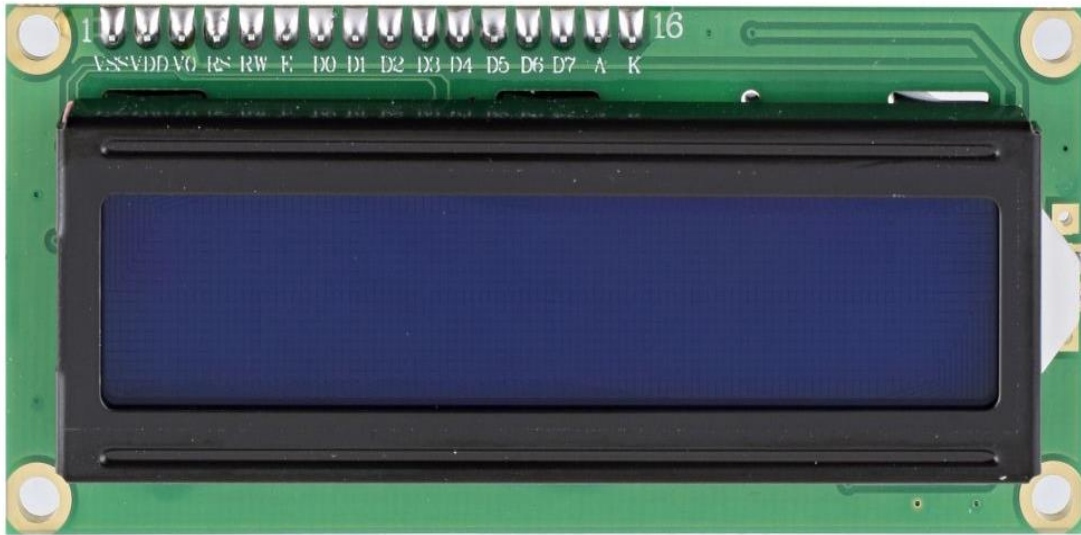


Fig:4.10 LCD Display

4.5.7 Heart Rate Sensor:

When a finger is placed on a heartbeat sensor, it produces a digital output of the heartbeat. The beat LED glows in unison with each heartbeat when the heartbeat detector is operational. To measure the Beats per Minute (BPM) rate, this digital output can be directly connected to the microcontroller. It works on the concept of blood flow via the finger modulating light at each pulse.



Fig: 4.11 Heart rate sensor

4.6 BLOCK DIAGRAM FOR HARDWARE:

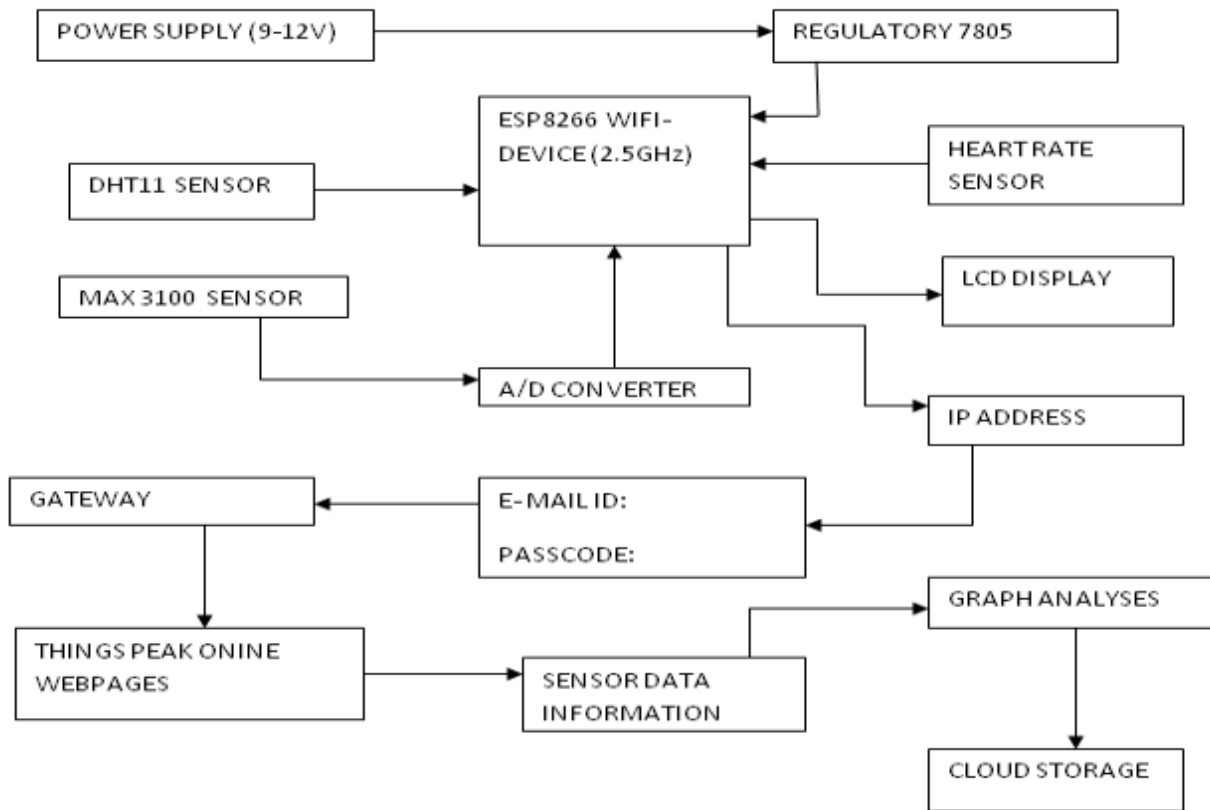


Fig:4.12 Schematic representation of Hardware

(fig: 4.11) Here we are using an ESP8266 WIFI Device or microcontroller with a frequency of 2.5ghz. Since we use this, we don't need any external converter, we use this for monitoring mode, the drawback of this is we have only 1 analog pin. We use a 9-12v power supply, it is connected with the regulator which helps us to convert from 12 to 5v. Then the regulator is connected to the microcontroller. It has 3 digital inputs that we use. In LCD we use a 16×2 display. Then DHT11 sensor is used to measure temperature & humidity. The MAX3100 is used for the spO2 sensor& also used to measure heart rate. Despite this Max sensor, we also added a heart rate sensor additionally.it acts as a photoelectric diode, to transmit and receive signals that are is transferred to analog to digital converter. Since our body signal is analog, we are using this to the converter to digital & send it back to the microcontroller. The final output is displayed on LCD. The microcontroller is connected with the webpage and we need to

enter the mail id and password, it acts as a gateway which is things peak online webpage. From there, we gather the information and based on their performance the graph is analyzed and it is stored in the cloud so that it can be accessed by everyone.

4.7 CIRCUIT DESCRIPTION:

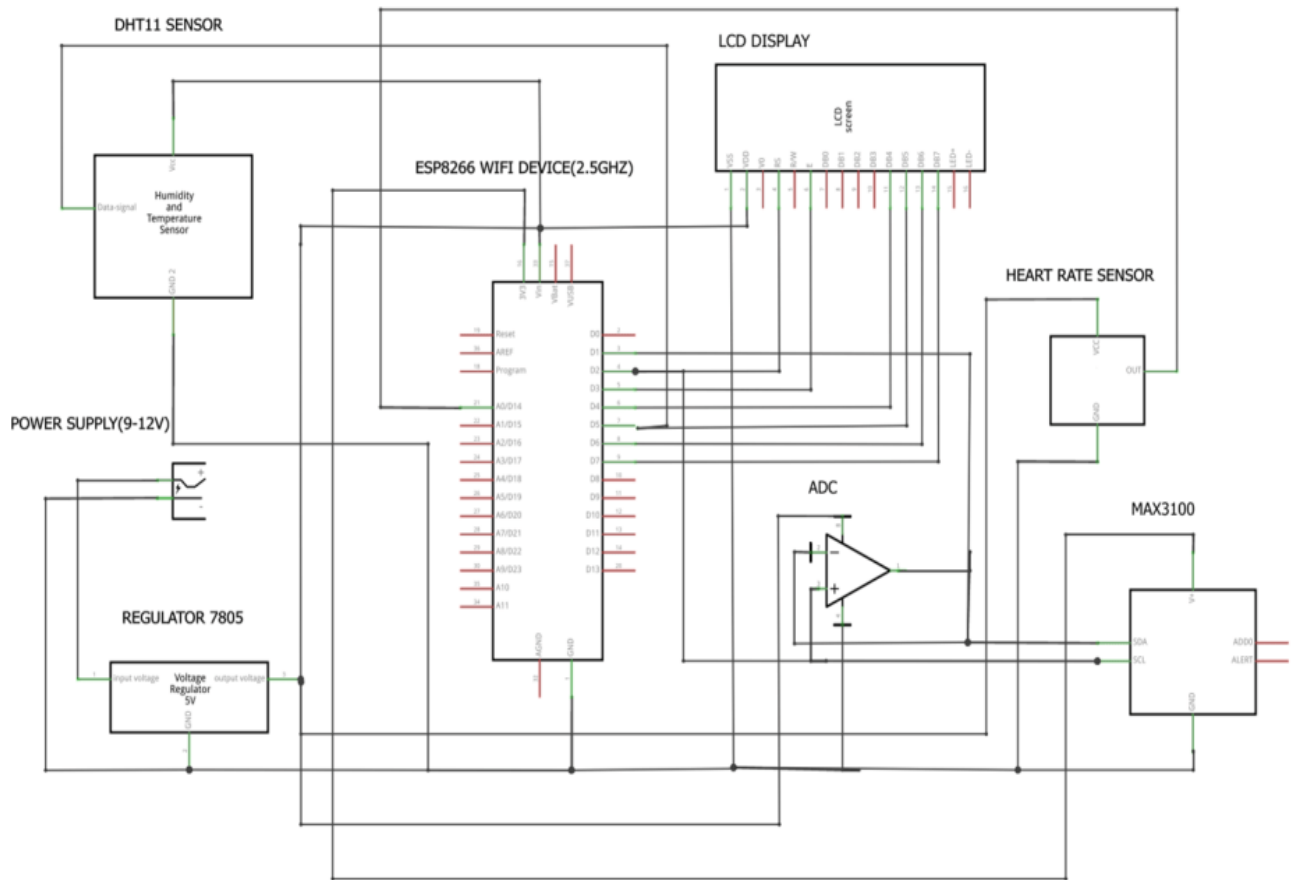


Fig:4.13 Circuit diagram of hardware

The above circuit (fig:4.12) consists of the core components of the ESP8266 Wi-Fi device, LCD, heart rate sensor, DHT11 sensor, MAX3100, ADC, power supply, and regulator. The 12v supply is converting to 5v with the help of voltage regulator 7805. Then the 5v supply is given to the Wi-Fi device. ADC for converting analog signal to digital signal from MAX3100. LCD Display is connected to Wi-Fi device digital pins like d2, d3, d4, d5, d6, d7 respectively. VSS is connected to the ground, and VDD is

connected to 5v. DHT11 sensor has 3 pins GND, VCC, and a data pin. VCC pin is connected to the 5v supply, the data pin is connected to the Wi-Fi device d5 pin, GND pin is grounded. The heart rate sensor has 3 pins GND, VCC, and OUT pin. VCC pin is connected to 5v supply, OUT pin is connected to Wi-Fi device analog pin, GND pin is grounded. MAX3100 sensor has 4 pins GND, V+, SCL, SDA.V+ pin is connected to 3.3V supply, SCL and SDA pins are connected to Wi-Fi device digital pins d1, d2, GND pin is grounded.

4.8 IoT:

The Internet of Things (IoT) refers to physical objects (or groups of such objects) that are equipped with sensors, faster processors, software, and other technologies and may communicate with other devices and systems over the Internet or other communication networks. The term "Internet of Things" has been deemed a misnomer because gadgets do not need to be connected to the public internet; instead, they must be connected to a network and addressed individually. Multiple technologies, including as ubiquitous computing, commodity sensors, increasingly powerful embedded systems, and machine learning, have influenced the field's evolution. The use of IoT is to establish links between the user and the physician to monitor the user's progress data. There are so many IoT pages available online but we preferred the Thing speak online web page.



web page of ThingSpeak

ThingSpeak for IoT Projects

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Non-commercial users may use ThingSpeak for free. Free accounts offer limits on certain functionality. Commercial users are eligible for a time-limited free evaluation. To get full access to the MATLAB analysis features on ThingSpeak, log in to ThingSpeak using the email address associated with your university or organization.

To send data faster to ThingSpeak or to send more data from more devices, consider the [paid license options](#) for commercial, academic, home and student usage.

Email

No account? [Create one!](#)

By signing in you agree to our [privacy policy](#).

Next

Step 1: Enter Mail ID

The diagram illustrates the data flow: Smart Connected Devices (represented by a cluster of devices) send data to the ThingSpeak cloud (labeled 'DATA AGGREGATION AND ANALYTICS'). From the cloud, data is then processed by MATLAB (labeled 'ALGORITHM DEVELOPMENT SENSOR ANALYTICS').

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Fig:4.14 (a) Procedure to access the data from Webpage-
Step-1: Enter the mail ID.


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To use ThingSpeak, you must sign in with your existing MathWorks account or create a new one.

Non-commercial users may use ThingSpeak for free. Free accounts offer limits on certain functionality. Commercial users are eligible for a time-limited free evaluation. To get full access to the MATLAB analysis features on ThingSpeak, log in to ThingSpeak using the email address associated with your university or organization.

To send data faster to ThingSpeak or to send more data from more devices, consider the [paid license options](#) for commercial, academic, home and student usage.

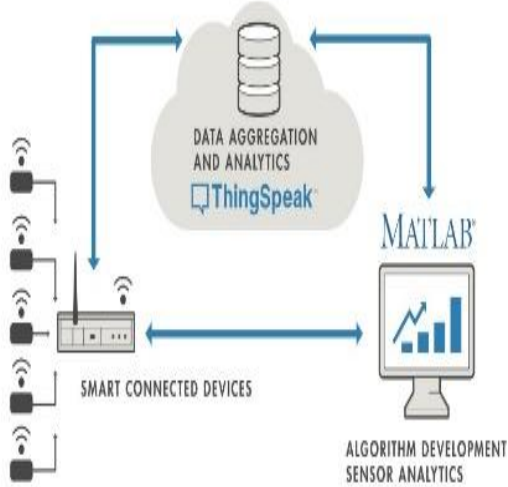


[← mercyjoshuasiki@gmail.com](#)

Password

[Forgot Password?](#)

Sign In



Step 1: Enter Passcode which act as gateway to online web page



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Fig:4.14 (b) Procedure to access the data from Webpage-
Step-1: Enter the passcode.

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Signed in successfully.

My Channels

New Channel

Name	Created	Updated
Virtual Safety Training System Using Machine Learning Private Public Settings Sharing API Keys Data Import / Export	2022-01-12	2022-02-07 06:22

Help

Collect data in a ThingSpeak channel from a device, from another channel, or from the web.

Click **New Channel** to create a new ThingSpeak channel.

Click on the column headers of the table to sort by the entries in that column or click on a tag to show channels with that tag.

Learn to [create channels](#), explore and transform data.

Learn more about [ThingSpeak Channels](#).

Examples

- [Arduino](#)
- [Arduino MKR1000](#)
- [ESP8266](#)
- [Raspberry Pi](#)
- [Netduino Plus](#)

After entering Mail ID and passcode, it leads to the webpage and information can be viewed

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X

Fig:4.14 (c) Procedure to access the data from Webpage-
Step-2: Press Enter which leads to the Web page.

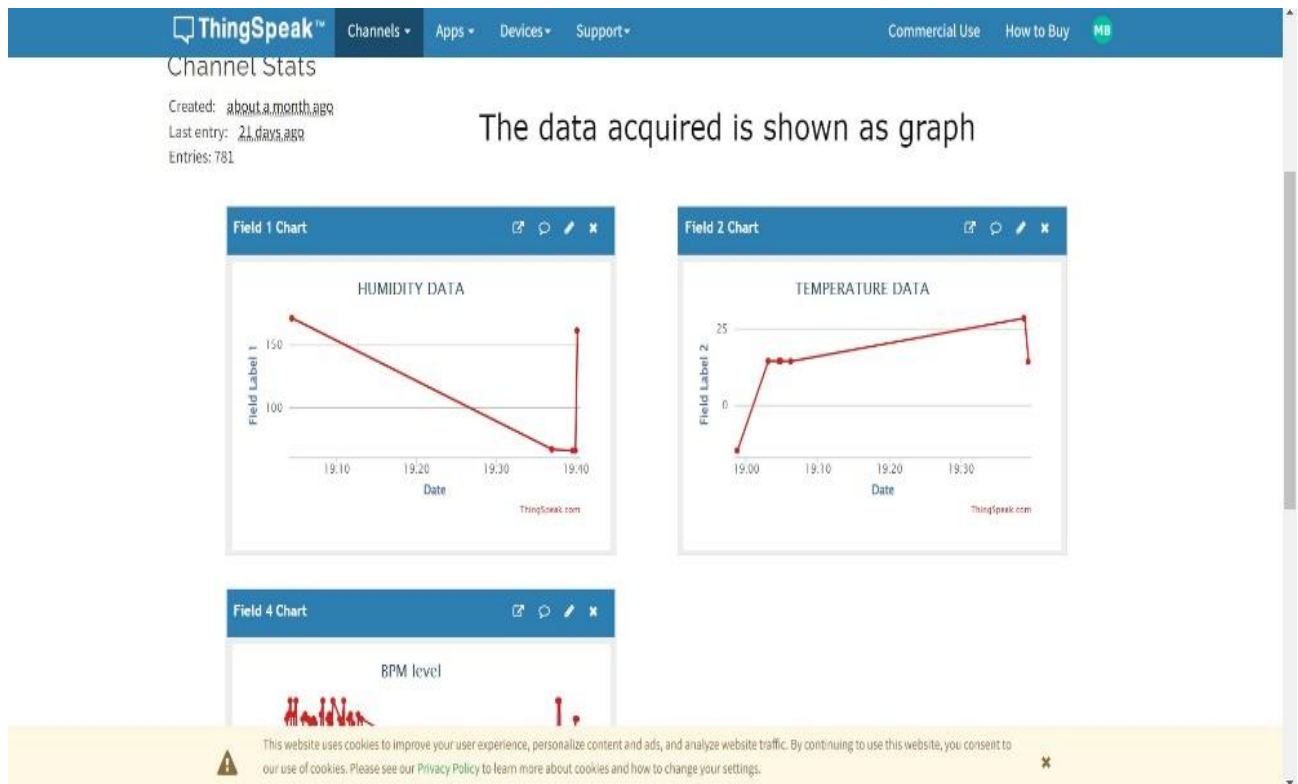


Fig:4.14 (d) Procedure to access the data from Webpage-

Step-3: Data verification from the Web page.

The above snapshot (fig:4.14) clearly explains the ThingSpeak online webpage procedure to access the data.

CHAPTER 5 – RESULTS

5.1 RESULTS:

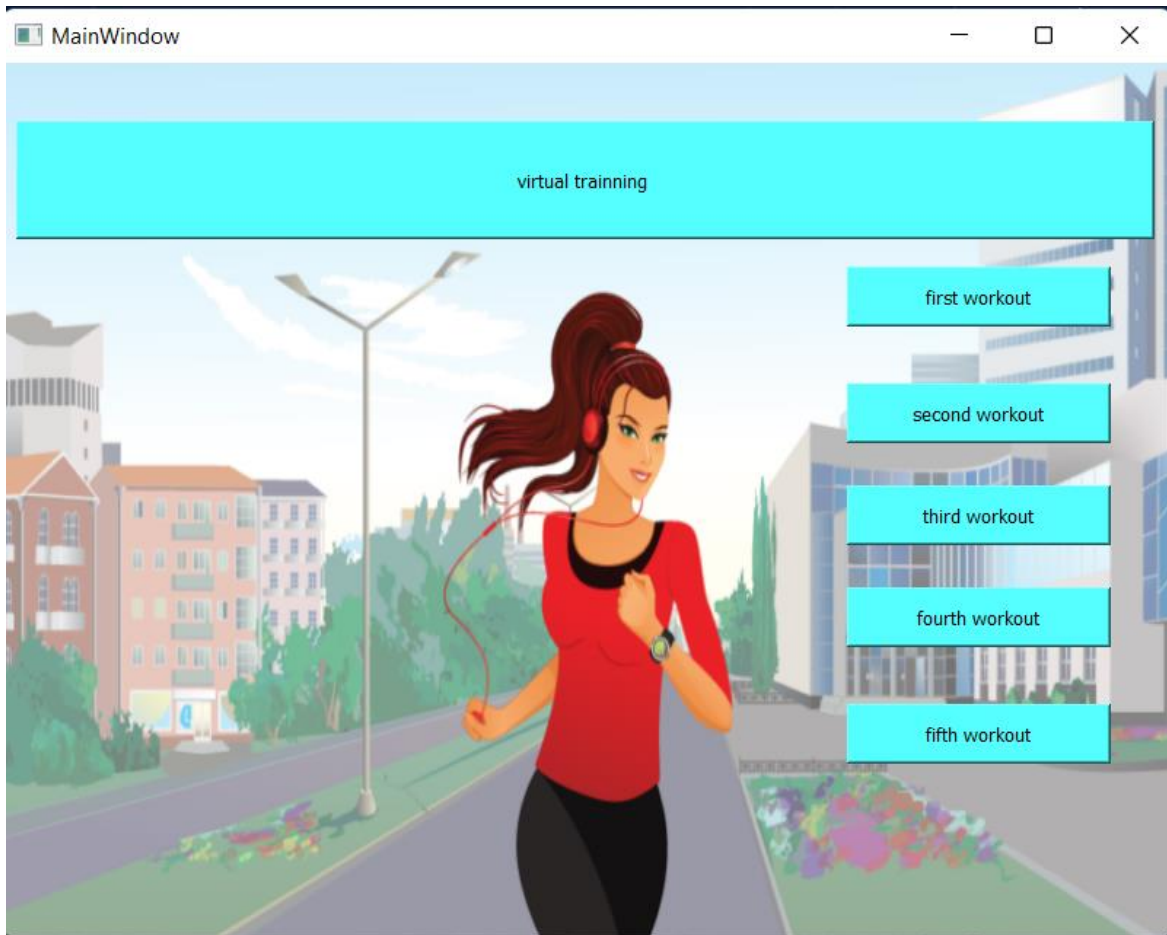


Fig: 5.1 (a) represents the various exercises of our work – Main window

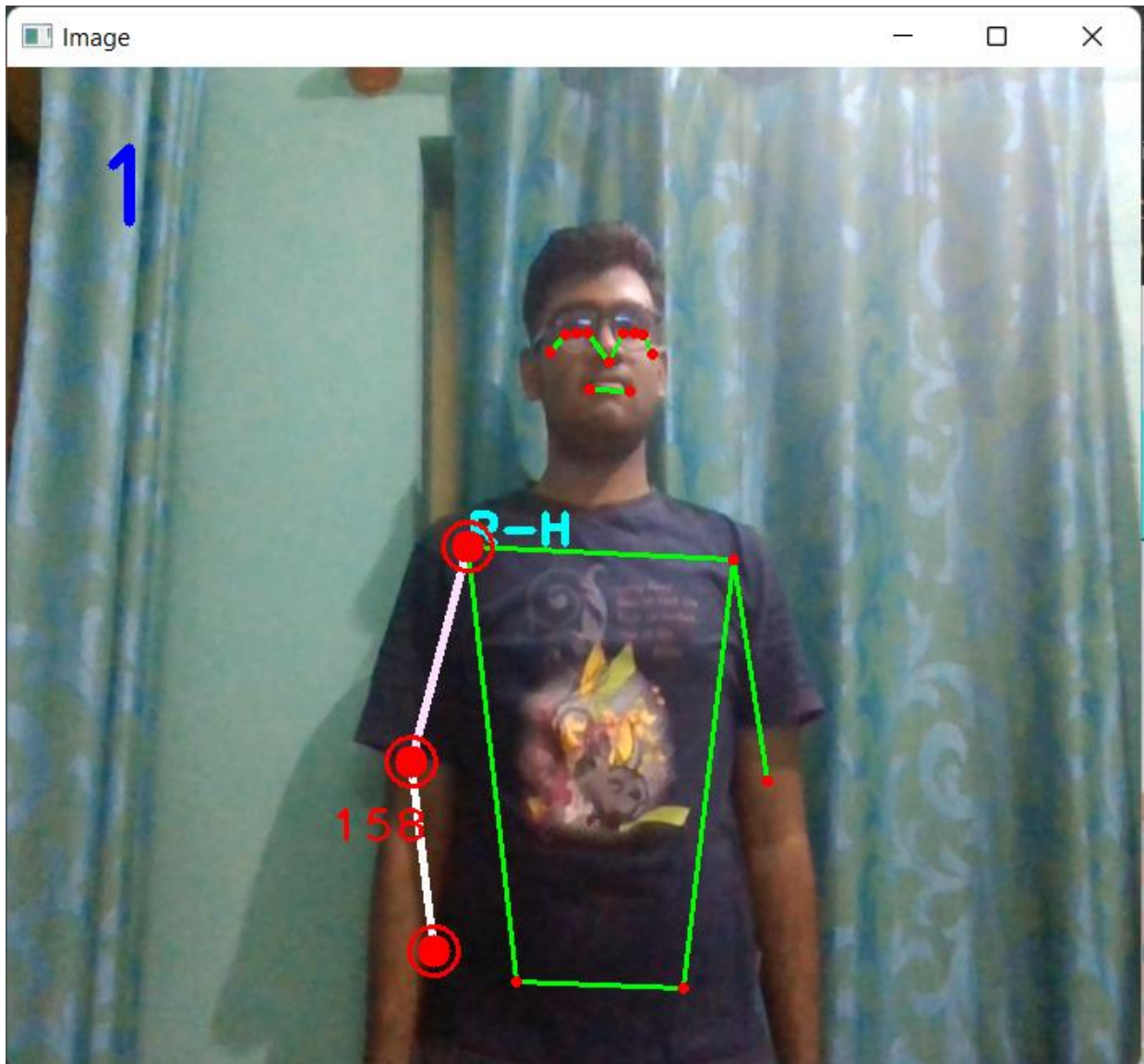


Fig: 5.1 (b) represents the various exercises of our work – exercise 1

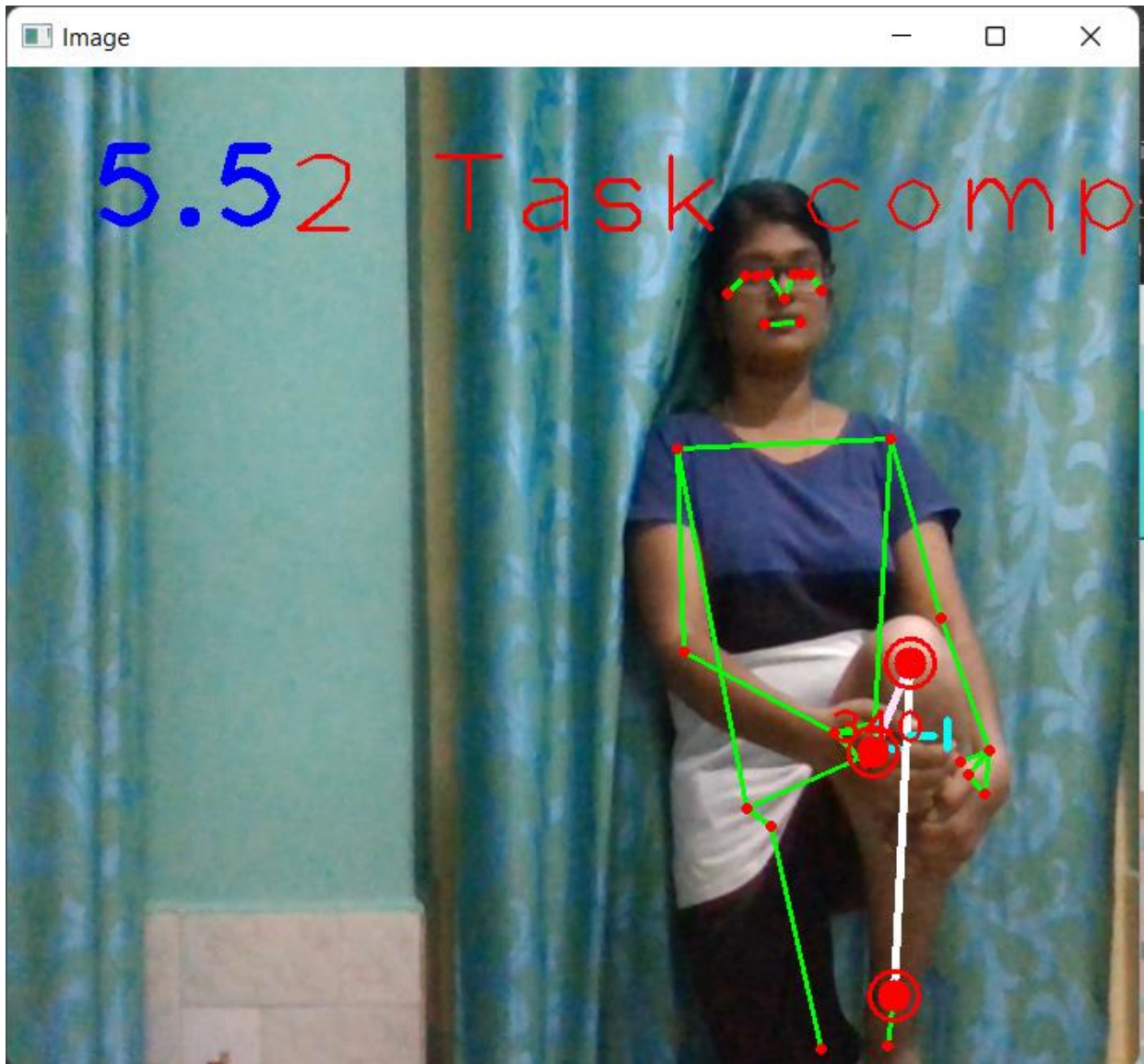


Fig: 5.1 (c) represent the various exercises of our work – exercise 2

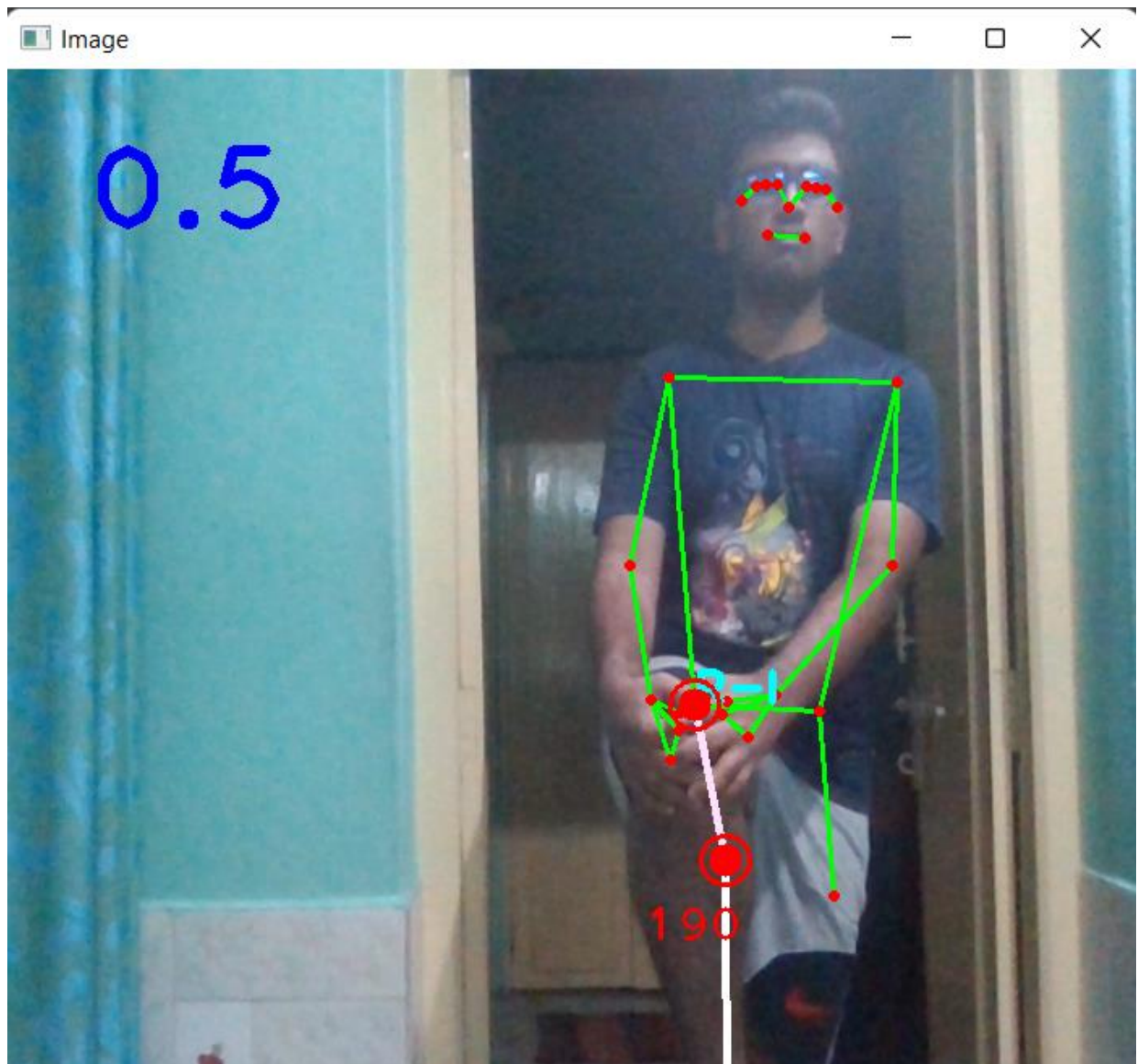


Fig: 5.1 (d) represents the various exercises of our work – exercise 3



Fig: 5.1 (e) represents the various exercises of our work – exercise 4

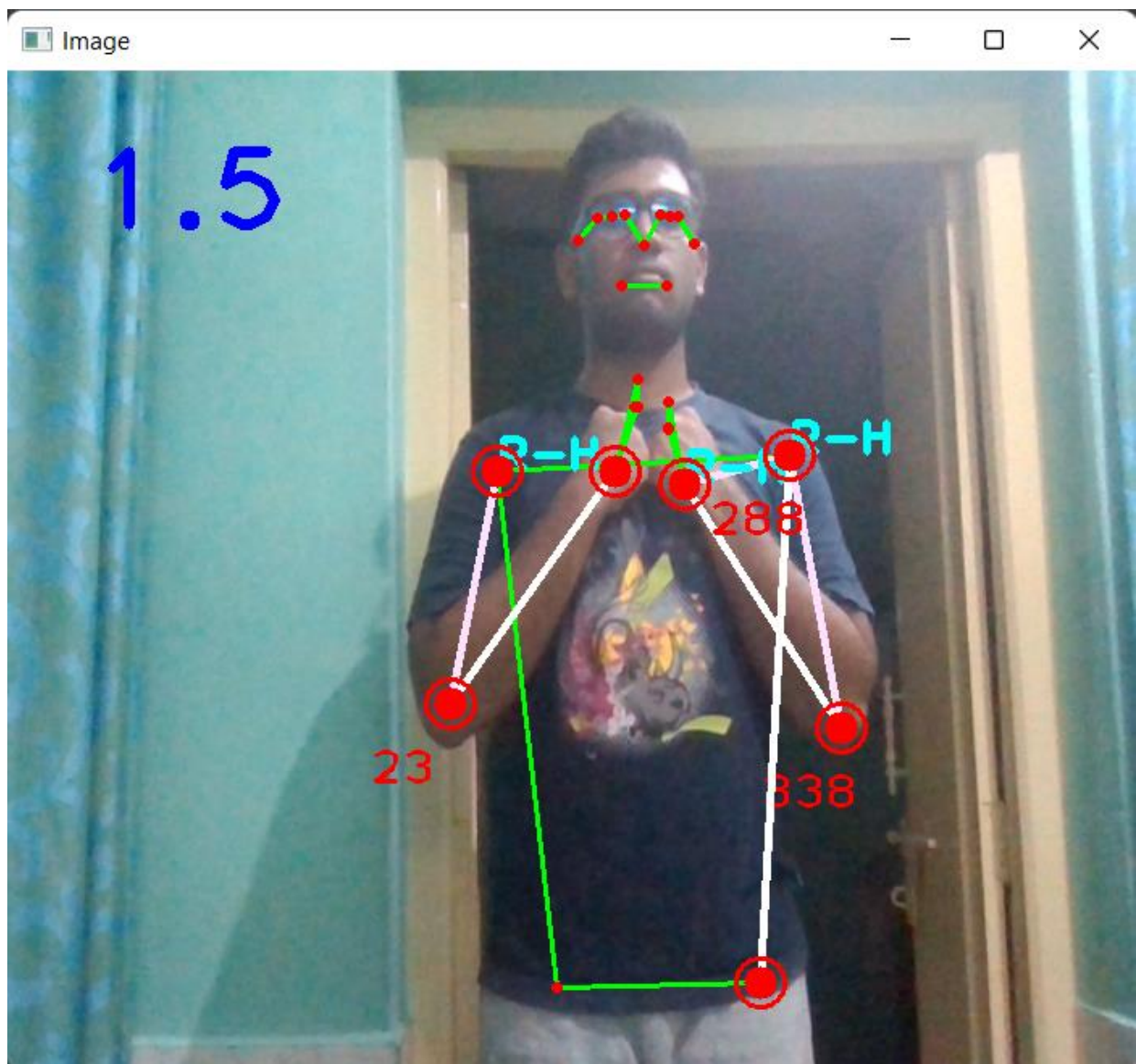
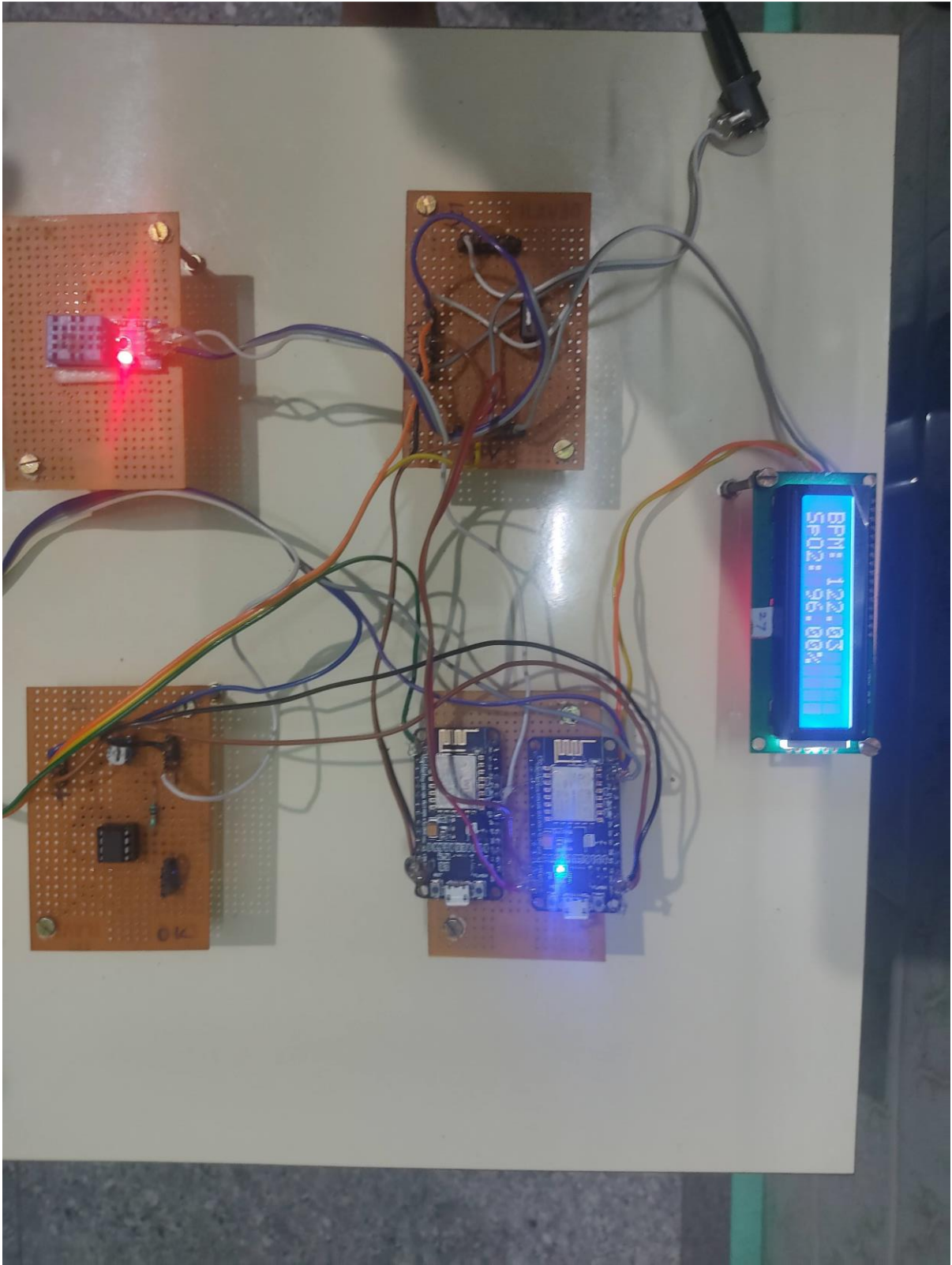


Fig: 5.1 (f) represent the various exercises of our work – exercise 5



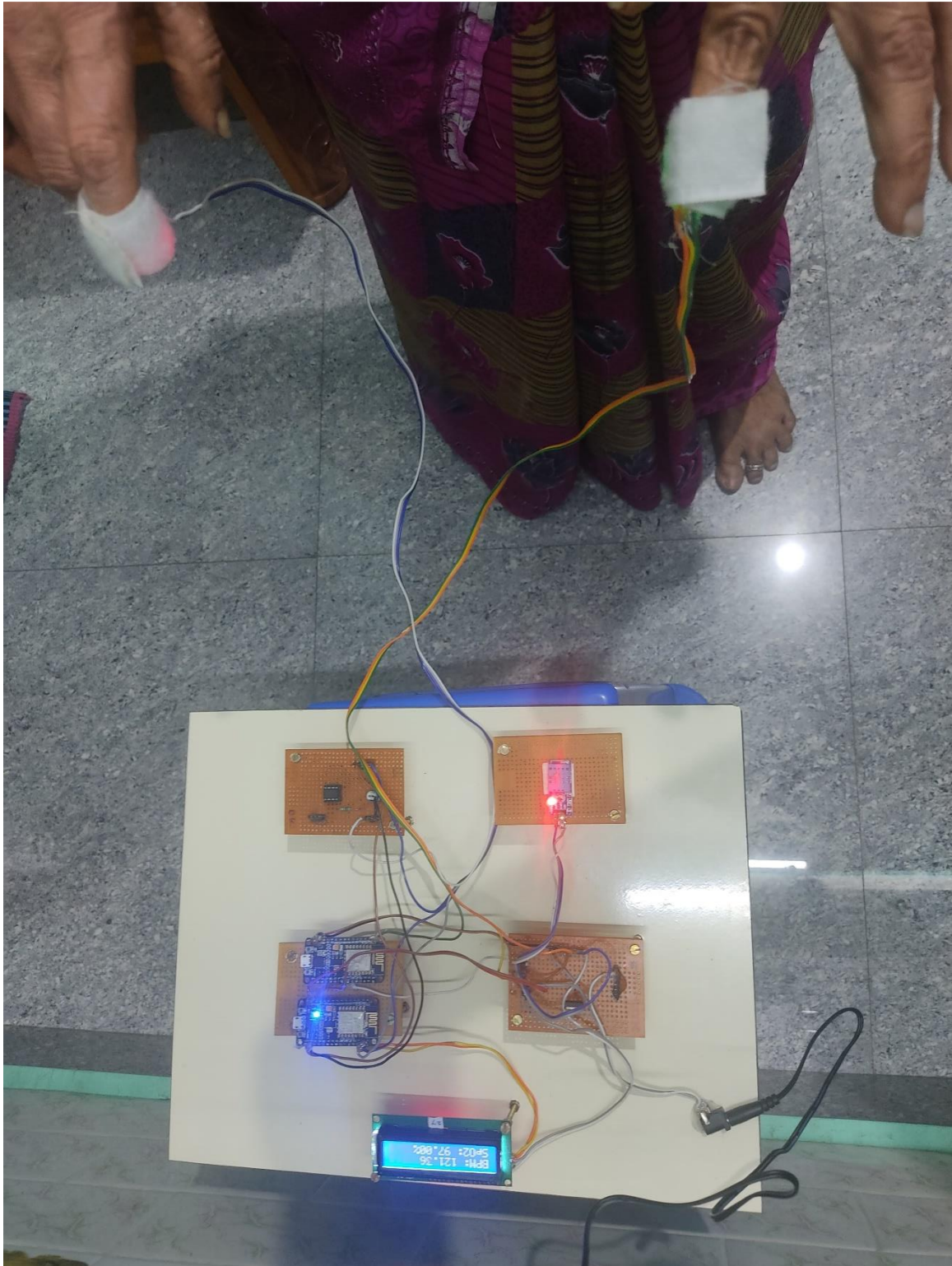


Fig: 5.2 Pictorial representation of hardware

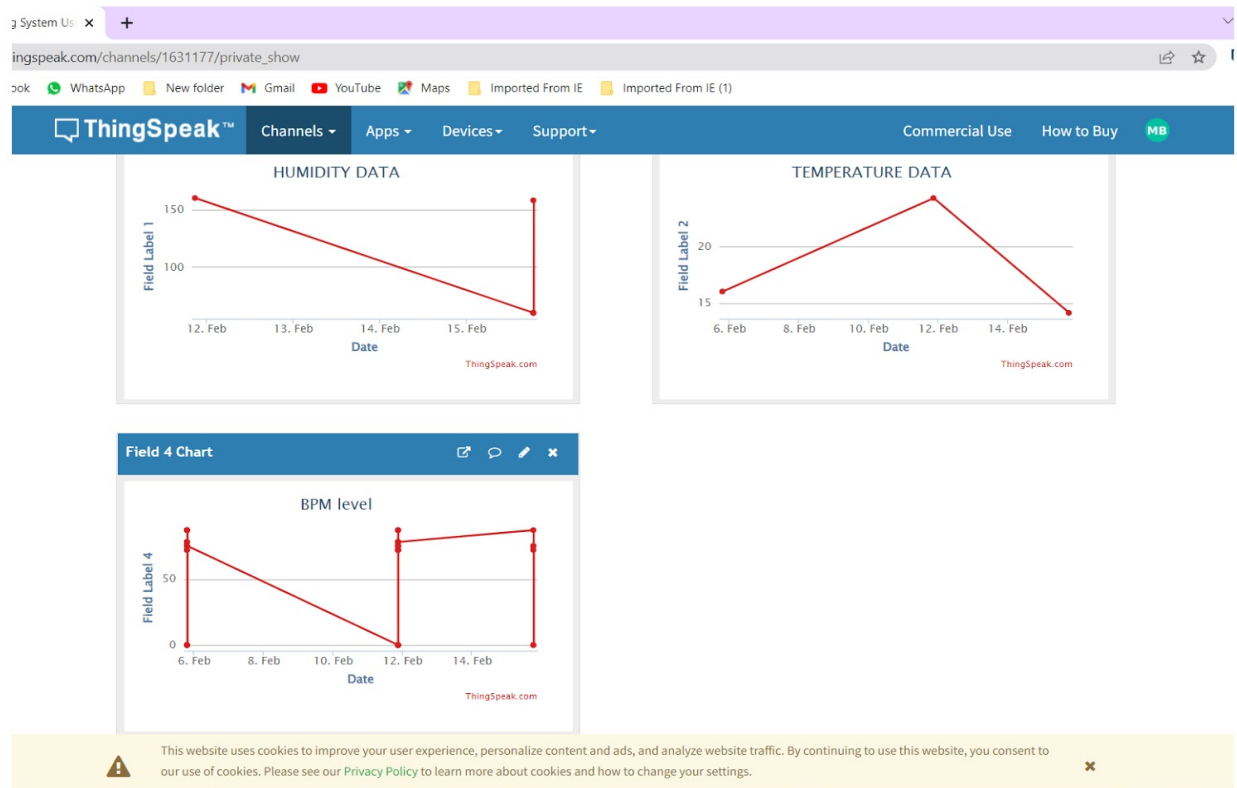
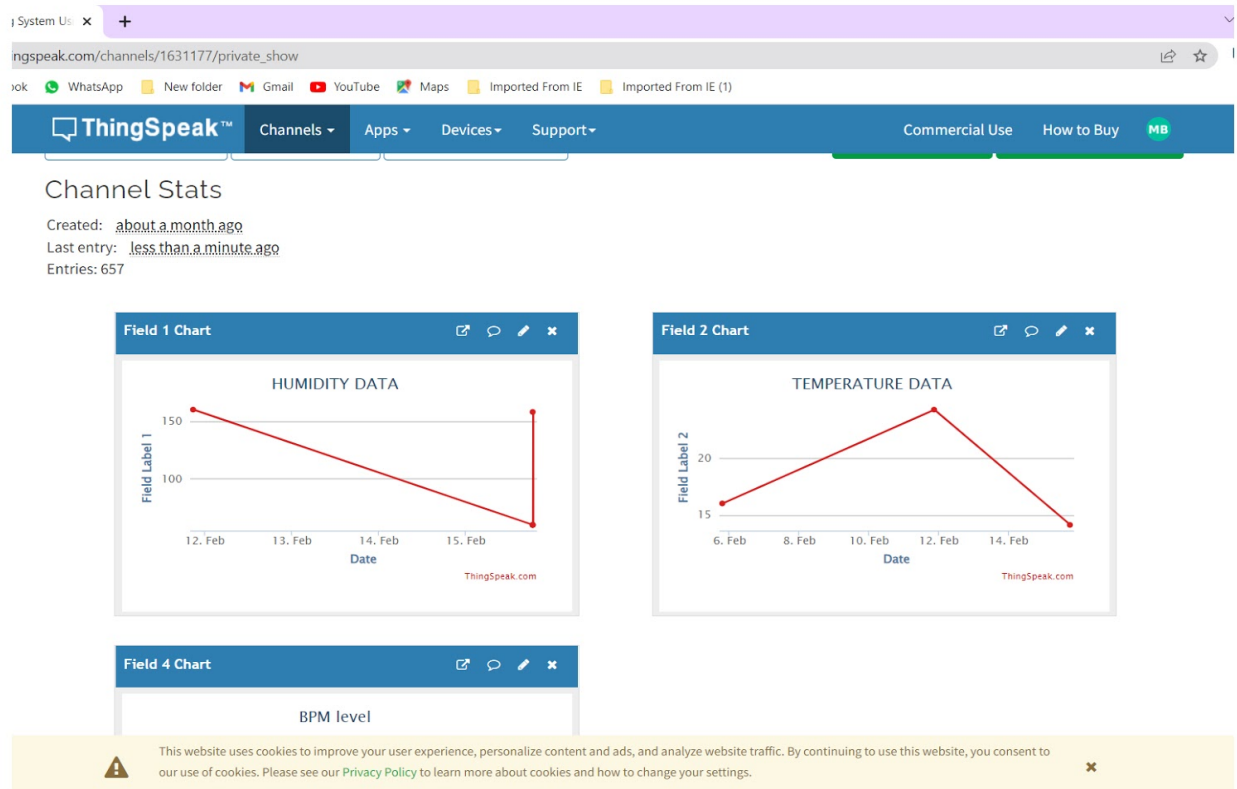


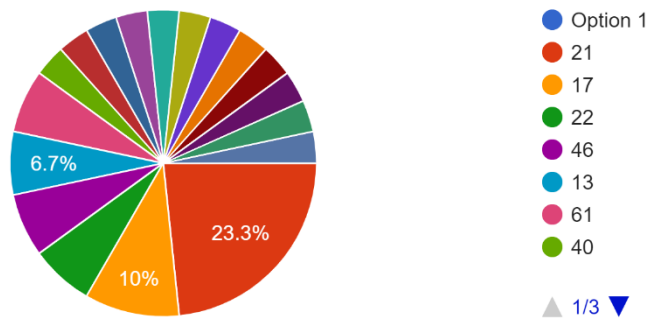
Fig: 5.3 ThingSpeak Online webpage

5.2 DISCUSSION:

We have taken data from various people in different categories and analyzed their performance. Accuracy of 95.3% and 99.4% is achieved for activity recognition and repetition count respectively.

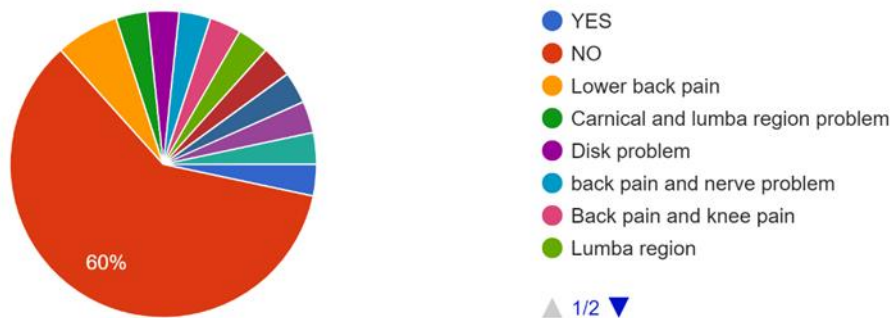
AGE

30 responses



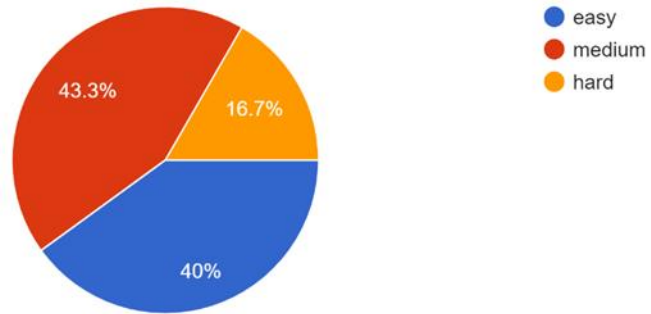
HEALTH ISSUES (if any specify)

30 responses



LEVEL OF PERFORMANCE

30 responses



DIFFICULTY FACED DURING EXERCISE

30 responses

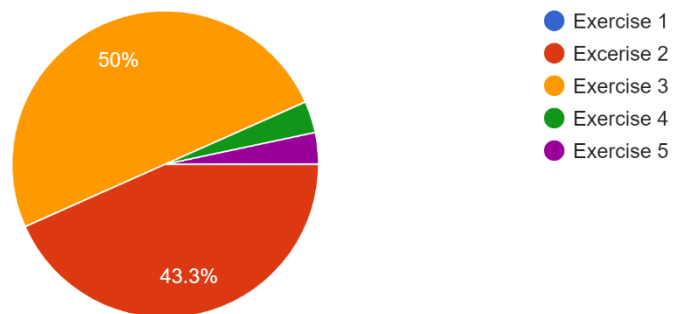


Fig: 5.4 results obtain from patients

CHAPTER 6 – CONCLUSION

The detection of the repetitions in a workout (physical) without requiring user intervention was carried out in our project by using the training data. Machine learning technology in this field could help the judges during exercise. In this project, we propose a multitask system including an off-the-shelf human pose estimation model and a multitask model of exercise recognition & repetition counting. In this work, we address the problem of the efficiency of exercise and calorie burn and boost the performance of the device it executes without any lagging. Unlike many existing systems, our proposed system was scalable, low-cost, and widely accessible. The project concluded the various support to the patients by providing proper teaching and verifying the proper form and independent journey in training. The kit helps the patients:

- The patients who can't come to the hospital
- Patients in absence of a physiotherapist
- Highly recommended for the high accuracy and helping the Patients in fast recovery

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