Virtual Safety Training System By Using Machine Learning

MERCY. S
Dept of Biomedical Engineering
School of Bio and Chemical Engineering,
Sathyabama Institute of Science and technology, Chennai-119

Abstract- *Despite numerous devices targeted to fitness tracking, the strength training domain has often been overlooked and understudied. We propose a camera-based approach to track users' strength training workouts and 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 and analyzes human pose points-based an angle-wise movement in the body. These results demonstrate that a commercial off-the-shelf camera can be used to detect and count repetition in user movements and to 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 the help of hardware called Node MCU (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 in the other end through the cloud. We analyze the recorded data to give suggestions about users' progress which helps in setting a goal for the future.*

Keywords- Artificial Intelligence, exercise, training module.

I. 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. 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 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. Machine learning (ML) is the study of computer algorithms that can learn and improve on their own given experience and data. 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. 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. A random forest algorithm is a machine learning technique that's used to solve regression and classification problems. With 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 the 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.

II. 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 verifying the proper form and independent journey in training.

III. 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

TECHNIQUE: Real-time approach to detect the 2D pose of multiple people in an image.

METHOD: 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. This bottom-up system achieves high accuracy and real-time performance.

RESULT: 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, JiayaJia. Human Pose Estimation with Spatial Contextual Information

TECHNIQUE: 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.

METHOD: Two conceptually simple and yet computationally efficient modules, namely Cascade Prediction Fusion (CPF) and Pose Graph Neural Network (PGNN), to exploit underlying contextual information.

RESULT: 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

TECHNIQUE: Deep convolutional neural networks are an effective way to improve the accuracy of human pose estimation.

METHOD: Cascade Feature Aggregation (CFA) method, which cascades several hourglass networks for robust human pose estimation.

RESULT: The extensive experiments on MPII datasets and LIP datasets demonstrate that 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

TECHNIQUE: The human pose estimation problem with a focus on learning reliable high-resolution representations.

METHOD: Multi-scale fusions such that each of the high-to-low resolution representations receives information from other parallel representations over and over, leading to rich high-resolution representations.

RESULT: As a result of this more accurate and spatially more precise.

5. Guanghan Ning, Heng Huang. LightTrack: A Generic Framework for Online Top-Down Human Pose Tracking

TECHNIQUE: Single-person Pose Tracking (SPT) and Visual Object Tracking (VOT) are incorporated into one unified functioning entity, easily implemented by a replaceable single-person pose estimation module.

METHOD: 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.

RESULT: This method outperforms other online methods while maintaining a much higher frame rate, and is very competitive with offline state-of-the-art.

IV. EXISTING METHOD

TECHNIQUE: Machine learning, Deep neural network(DNN), Convolution neural network(CNN), Fully Convolutional 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, ResNet-50- 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 with high accuracy and spatially more precisely 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.

V. 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 them efficiently achieve their goals. Monitoring the heart rate allows 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 the wearable device on the body. As the 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 a 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.

VI. BLOCK DIAGRAM OF SOFTWARE

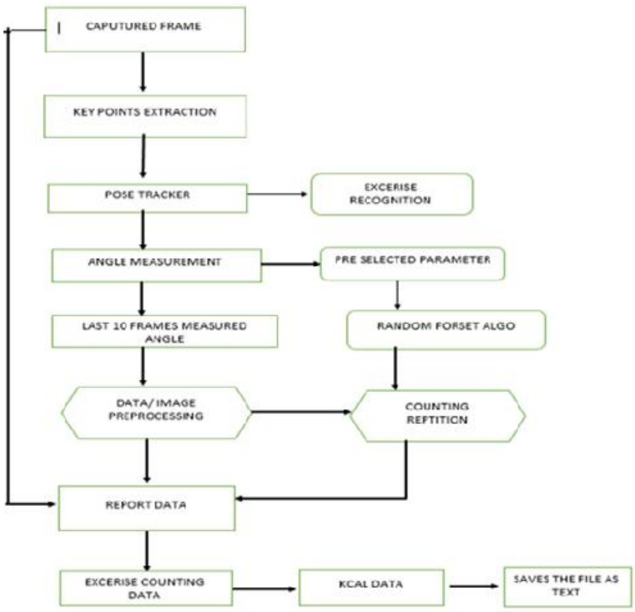

Fig:1 Schematic Representation of software execution

The above picture (fig:1) 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, 1to 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, after completion the data is reported. The exercise counting data & calorie data saves these files as text.

VII. BLOCK DIAGRAM FOR HARDWARE

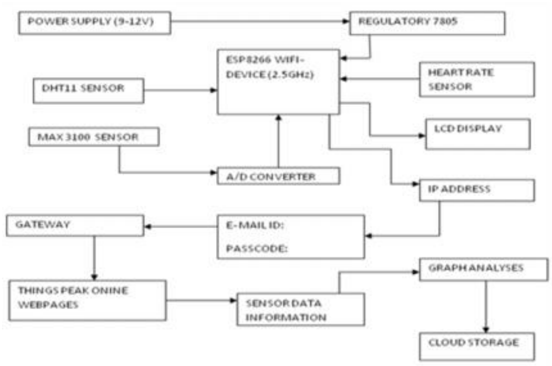

Fig:2 Schematic Representation of hardware

(fig: 2) 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 with 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 sp02 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 in 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, based on their performance the graph is analyzed and it is stored in the cloud so that it can be accessed by everyone.

VIII. CIRCUIT DESCRIPTION

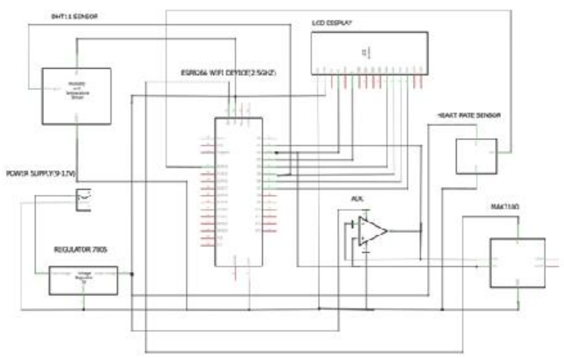

Fig: 3 Circuit diagram of hardware

The above circuit (fig:4.12) consists of the core components of ESP8266 Wi-Fi device, LCD, heart rate sensor, DHT11 sensor, MAX3100, ADC, power supply, 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, VDD is connected to 5v. DHT11 sensor has 3 pins GND, VCC, data pin. VCC pin is connected to 5v supply, the data pin is connected to Wi-Fi device d5 pin, GND pin is grounded. The heart rate sensor has 3 pins GND, VCC, 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.

IX. IOT (INTERNET OF THINGS)

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. 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 Thing speak online web page.

X. RESULTS

Fig: 4 represent the various exercises of our work

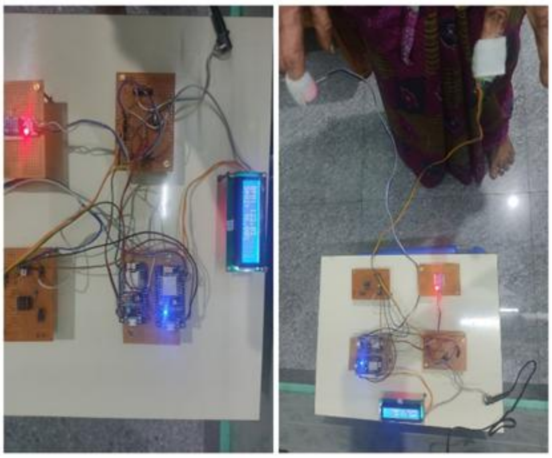

Fig: 5 Pictorial representation of hardware

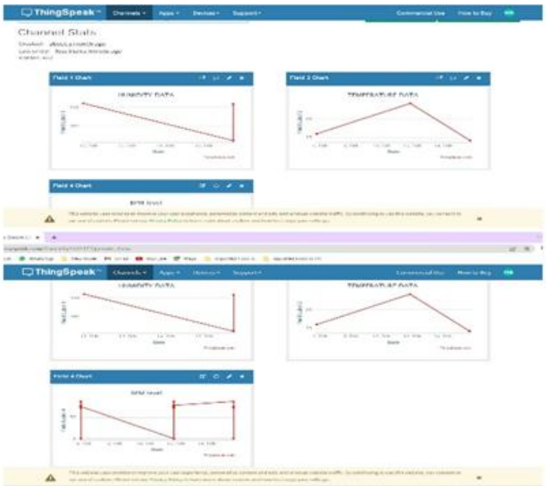

Fig: 6 ThingSpeak Online webpage

10.1 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.

XI. CONCLUSION

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.

REFERENCES

[1] Ana Pereira and Carsten Thomas," Challenges of Machine Learning Applied to Safety-Critical Cyber-Physical Systems", 2020, doi:10.3390/make2040031.

[2] B. Artacho and A. Savakis, "UniPose: Unified Human Pose Estimation in Single Images and Videos," 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2020, pp. 7033-7042, DOI: 10.1109/CVPR42600.2020.00706.

[3] A. Bulat, J. Kossaifi, G. Tzimiropoulos, and M. Pantic, "Toward fast and accurate human pose estimation via soft-gated skip connections," 2020 15th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2020), 2020, pp. 8-15, DOI: 10.1109/FG47880.2020.00014.

[4] Bruno Artacho and Andreas Savakis, "OmniPose: A Multi-Scale Framework for Multi-Person Pose Estimation", 2021, ArXiv, Volume: abs/2103.10180.

[5] B. Cheng, B. Xiao, J. Wang, H. Shi, T. S. Huang, and L. Zhang, "HigherHRNet: Scale-Aware Representation Learning for Bottom-Up Human Pose Estimation," 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2020, pp. 5385-5394, DOI: 10.1109/CVPR42600.2020.00543.

[6] Chen, Steven & Yang, Richard., Pose Trainer: Correcting Exercise Posture using Pose Estimation, 2018.

[7] Z. Cao, T. Simon, S. Wei, and Y. Sheikh, "Realtime Multi-person 2D Pose Estimation Using Part Affinity Fields," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017, pp. 1302-1310, DOI: 10.1109/CVPR.2017.143.

[8] Dreossi, Tommaso; Donzé, Alexandre; Seshia, Sanjit A. (2019). Compositional Falsification of Cyber-Physical Systems with Machine Learning Components. Journal of Automated Reasoning, doi:10.1007/s10817-018-09509-5.

[9] Fuat., Google Colab Free GPU Tutorial, 2018. https://medium.com/deep-learning-turkey/google-colab-free-gpu-tutorial-e113627b9f5d

[10] Hong Zhang, Hao Ouyang, Shu Liu, Xiaojuan Qi, Xiaoyong Shen, Ruigang Yang, JiayaJia," Human Pose

Estimation with Spatial Contextual Information”, 2019, ArXiv, Volume: abs/1901.01760.

[11] Hanczar, B & Dougherty, E., Classification with reject option in gene expression data, 2018.

[12] D. Huang, X. Wang, J. Li, and W. Tang, "Virtual Reality for Training and Fitness Assessments for Construction Safety," 2020 International Conference on Cyberworlds (CW), 2020, pp. 172-179, DOI: 10.1109/CW49994.2020.00036.

[13] Khurana R., Ahuja K., Yu Z., Manko J., Harrison C., &Goel M., GymCam: Detecting, Recognizing and Tracking Simultaneous Exercises in Unconstrained Scenes, 2018.

[14] Kim I., Deep Pose Estimation implemented using Tensorflow with Custom Architectures for fast inference, 2018.

[15] Krishnan M., Using the law of cosines and vector dot product formula to find the angle between three points, 2019.

[16] W. -N. Lie, G. -H. Lin, L. -S. Shih, Y. Hsu, T. H. Nguyen, and Q. Nguyen QuangNhu, "Fully Convolutional Network for 3D Human Skeleton Estimation from a Single View for Action Analysis," 2019 IEEE International Conference on Multimedia & Expo Workshops (ICMEW), 2019, pp. 1-6, DOI: 10.1109/ICMEW.2019.0-120.

[17] MichailPavlou, DimitriosLaskos, Evangelia I. Zacharaki, Konstantinos Risvas, and Konstantinos Moustakas,” An XR training system for interactive simulation and ergonomics assessment”, 2021, https://doi.org/10.3389/frvir.2021.646415

[18] Martinez J., Hossain R., Romero J., & Little J., A simple yet e ective baseline for 3d human pose estimation, 2017.

[19] 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”, 2019, VL- 229, DO - 10.1016/j.knosys.2021.107388

[20] G. Ning, J. Pei, and H. Huang, "LightTrack: A Generic Framework for Online Top-Down Human Pose Tracking," 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2020, pp. 4456-4465, DOI: 10.1109/CVPRW50498.2020.00525.

[21] Ongdong Yu, Kai Su, Changhu Wang.” Towards Good Practices for Multi-Person Pose Estimation”, 2019, ArXiv, Volume: abs/1911.07938.

[22] Soomro K., Roshan A. & Shah M., UCF101: A Dataset of 101 Human Action Classes from Videos in The Wild, 2019.

[23] Soro, A., Brunner, G., Tanner, S., &Wattenhofer, R. Recognition and Repetition Counting for Complex Physical Exercises with Deep Learning. 2019.

[24] K. Sun, B. Xiao, D. Liu, and J. Wang, "Deep High-Resolution Representation Learning for Human Pose Estimation," 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 5686-5696, DOI: 10.1109/CVPR.2019.00584.

[25] Y. Tanaka and M. Hirakawa, "Efficient strength training in a virtual world," 2016 IEEE International Conference on Consumer Electronics-Taiwan (ICCE-TW), 2016, pp. 1-2, DOI: 10.1109/ICCE-TW.2016.7521030.

[26] Walker, E. Are You Ready to Judge? 2020. http://www.crossfit1864.com/blog/2016/2/26/29-feb-2016-are-you-ready-to-judge

[27] Zhe C., Tomas S., Shih-En W., &Yaser S., OpenPose: RealtimeMultiperson 2D Pose Estimation using Part A nity Fields, 2018.

[28] Zhe C., Tomas S., Shih-En W., &Yaser S., OpenPose - Frequently Asked Question (FAQ), 2019.

[29] Zhihui Su, Ming Ye, Guohui Zhang, Lei Dai, Jianda Sheng,” Cascade Feature Aggregationfor Human Pose Estimation”,2019, ArXiv, Volume: abs/1902.07837.

[30] F. Zhang, X. Zhu, H. Dai, M. Ye, and C. Zhu, "Distribution-Aware Coordinate Representation for Human Pose Estimation," 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2020, pp. 7091-7100, DOI: 10.1109/CVPR42600.2020.00712.