AMRUTVAHINI COLLEGE OF ENGINEERING, SANGAMNER

INTERNATIONAL CONFERENCE ON RECENT TRENDS AND ADVANCEMENTS IN COMPUTING TECHNOLOGIES,ICRTACT 2024

PoseCraft Fitness Navigator: A Flask integrated AI System for yoga and exercise monitoring.

Shubhada Mone[1], Atharva Yanna[2], Pratham Kotkar[3], Kabir Kapse[4], and Om Jagtap[5]
Computer Science Department, Marathwada Mitra Mandals College of Engineering, Pune, India
Email: shubhadamone@mmcoe.edu.in[1], atharvay24@gmail.com[2], prathampkotkar@gmail.com[3],kabirkapse111@gmail.com[4], omjagtap15@gmail.com[5]

***Abstract*—This paper provides an in-depth examination of the most recent advancements in fitness tracking and posture correction technology. The use of these technologies has grown dramatically during a period of time when people are paying more attention to their personal health and wellness. The report looks at a range of advancements, from sensor-based systems to Computer Vision applications, outlining their advantages and disadvantages. It provides light on the benefits of posture correction techniques and how they impact training routines by combining data from numerous research and commercial products. It also discusses more recent innovations, such as AI-driven virtual fitness assistants and the integration of mindfulness practices like Yoga and Meditation into fitness regimens. The purpose of this study is to provide useful information to academics, professionals, and people who want to make informed judgments.**

***Index Terms*—Computer Vision, Deep Learning, Flask, MediaPipe, OpenCV**

I. Introduction

In the 21st century, where health and technology innovation converge, maintaining an active and healthy lifestyle is becoming more and more essential to day-to-day existence. People around the world strive to be physically active not only to improve their physical capabilities but also to support their mental and emotional well-being. In this regard, we provide a novel technological development, the" Pose-Craft Navigator." The research we are conducting dives further into this game-changing application, imagining it as a real-time, multifunctional real-time solution that counts repetitions precisely, monitors workout postures intimately, and integrates yoga and meditation modules with ease. This innovative application has the potential to revolutionize exercise regimens and advance holistic well-being, ushering in a new age of health consciousness and enabling people to embark on life-changing journeys toward the best possible physical and mental wellness.

In a society where technology affects every aspect of existence, the Pose-Craft Navigator represents the meeting point between scientific advancement and the age-old quest of well-being. Considering exercise to be the foundation of physical health, the app serves as a specialized virtual coach, offering in-the-moment feedback and posture modifications. It lowers the chance of injury and maximizes muscle engagement by addressing underlying issues, which increases the efficacy of exercises. Exercise routines gain motivation when repetitions are precisely counted, which guarantees accurate progress tracking.

This innovative app takes a comprehensive approach by including yoga and meditation sessions in addition to standard workouts. Recognizing the connection between mental and physical well-being, Pose-Craft Navigator gives users the tools to go on life-changing adventures that promote mental and physical well-being via guided sessions and mindfulness practices. Its goal is to establish a well-rounded way of living that goes beyond physical fitness. The app's emphasis on mindfulness practices, including meditation and yoga, serves as a powerful antidote to the stresses of modern life. By integrating moments of tranquility and self-reflection, Pose- Craft Navigator empowers users to manage stress, improve focus, and cultivate a positive mindset, ultimately contributing to a more resilient and balanced lifestyle.

The Pose-Craft Navigator represents a revolution in the way people interact with exercise and health regimens by combining state-of-the-art artificial intelligence with real-time monitoring. The program gathers useful data in addition to provide individualized assistance thanks to Flask integration. This adds to the continuing conversation about using technology to live healthier, more satisfying lives. Pose-Craft Navigator, which has been merged with Flask, is ready to usher in a new era of integrated well-being, in which people may use technology to maximize their mental and physical health, which will ultimately lead to a better and more joyful society.

Our research aims to dig even farther into the complex architecture, underlying technologies, and algorithms that power the Pose-Craft Navigator, since we regard it as a revolutionary force at the nexus of technology and well-being. We hope to make a substantial contribution to the growing conversation about how technology may be used to promote happier, healthier lives by comprehending the subtleties of its potential. The Pose-Craft Navigator, which embodies the revolutionary power of technology in creating a better, healthier future, emerges as a beacon directing people toward holistic wellness as we navigate a world where self-care and well-being take center stage.

In conclusion, Pose-Craft Navigator is a complete wellness platform that extends beyond the physical world, not merely a fitness app. It aims to rethink health by recognizing the con- nection between mental and physical well-being and inspiring users to go on life-changing journeys that result in a more contented and balanced way of living.

This section describes the multi-person pose estimation process provided by Hao-Shu Fang et al. [1], as well as the problems with classic soft-argmax keypoint regression and creative solutions. The gradient asymmetry and size-dependent keypoint scoring concerns are addressed with the symmetric integral keypoints regression technique. To distinguish joint confidence prediction from integral regression, it uses ampli- tude symmetric gradients (ASG) to improve gradient stability. The section also addresses part-guided proposal creation for training samples with distributions close to human detec- tor outputs, as well as multi-domain knowledge distillation for network training. Finally, parametric pose non-maximum suppression (NMS) is offered to eliminate redundant pose estimations by optimizing removal criteria based on data.This comprehensive technique improves multi-person posture esti- mation performance, making it more reliable and exact.

Keze Wang et al [2] introduces a 3D human pose machine that is capable of comprehensively integrating long-range spatio-temporal relationships and 3D geometry information. A unique self-supervised correction method is added to the model, involving two dual learning tasks: 3D-to-2D pose projection and 2D-to-3D pose transformation.

Hustinawaty et al. [3] developed an application that uses MediaPipe for pose detection and OpenCV to record video from a camera. The technique begins with OpenCV capturing the video input, which is then processed by MediaPipe to extract the x, y, and z coordinates of joints, focusing on the left and right knees and the center hip. These coordinates are used to determine the vectors of the left and right legs, as well as the angle between them.The result is placed on the video frame. The application is designed to detect movements using webcam images in a clinical setting with adequate lighting and a distance of 2.5-3 meters from the patient's bed. Before the motion capture process begins, users are asked to enter patient information. Straight Leg Raise Test (SLRT) postures are detected with image processing software, and range of motion (ROM) angles are calculated for analysis. The results, which include the patient's name, ROM angles, the presence of pain, and the diagnosis of sciatica, are recorded in a database for future research.

The four primary steps of the methodology described by Venkata Sai P Bhamidipati et al. [4] for creating a reliable pos- ture estimate system for an AI gym trainer utilizing Mediapipe and OpenCV are data collecting, data preprocessing, pipeline training, and pipeline evaluation.

In order to overcome this, Tong Zhang et al. [5] have sug- gested a novel top-down convolutional network that combines a discriminator network with previous knowledge of pose structure acquired through adversarial learning. This method outperforms earlier approaches in tasks like MS COCO human key point identification, displaying efficiency and efficacy in pose prediction. It also improves robustness in difficult real- world circumstances.

Filippos Markolefa et al. [6] suggest a new way for improv- ing online training videos: overlaying the trainee's silhouette for easy comparison with the trainer. It combines different techniques for background modeling and foreground extrac- tion, solving issues such as slow-moving objects and lighting changes.

Different neural network architectures, including CNNs, RNNs, and GANs, as well as artificial intelligence models, including self-aware AI and reactive machines, are covered by Nachaat Mohamed et al. [7]. It describes its uses in language modeling and picture recognition, for example, and suggests an integrated method dubbed AINNA to merge AI with natural language processing for improved outcomes, particularly in facial recognition tasks.

Rohit Girdhar et al. [8] propose a two-stage strategy for efficient and accurate human position monitoring across time. In the first stage, they use a 3D human posture predictor built on an expanded Mask R-CNN model that adds spatiotemporal operations by transforming 2D convolutions to 3D. This model takes brief video clips as input and predicts positions for all persons using temporal information, outperforming its 2D version. To track individuals across frames, a lightweight op- timization connects these posture predictions while resolving complexity concerns. They use a heuristic to attain state- of-the-art accuracy on the PoseTrack benchmark while dra- matically increasing computational efficiency over previous approaches. To achieve robust tracking and pose prediction, the approach integrates 3D convolutional networks, tube proposal networks, and anchor-based regression.

Ashish Gupta et al. [9] outlines the creation of a YogaHelp system intended at supporting amateur practitioners in learning the proper execution of yoga without the need for a trainer, which is especially important during times like a pandemic when in-person supervision is limited. The system detects the 12 linked-steps of sun salutation, a basic yoga sequence, using motion sensors like accelerometers and gyroscopes. While previous exercise recognition systems based on deep neural networks are effective at identifying activities, they lack the capacity to judge execution accuracy, which is critical for amateurs. YogaHelp bridges this gap by offering feedback on the appropriateness of yoga poses, boosting both the physical and mental health advantages of yoga practice.

A model that estimates joint depths to predict a 3D human location from a 2D input was proposed by Bruce Xiaohan Nie et al. [10]. It employs a two-stage LSTM architecture, gathering global and local data at the first level by merging a patch-LSTM and a skeleton-LSTM. A tree-structured LSTM efficiently propagates contextual information via joints. Depth prediction is achieved by augmenting the second-level LSTM with a fully-connected layer. This approach allows for inde- pendent 2D pose estimation and depth prediction, providing flexibility for implementing improvements in 2D pose estimate methodologies. The model outperforms flat structures, proving the usefulness of the tree-structured LSTM in human location estimation.There are three phases to the model's learning process: pre-training of the LSTM skeleton

The suggested Vyayam architecture model by Samhitha G et al. [11] uses real-time video input to track exercise regimens. It uses MediaPipe to build a virtual skeleton of the exercising individual and identify particular joints or keypoints that correspond to the exercise being done. The exercise count is tracked and increased by the model by computing the angles between these keypoints and showing the result to the user. Additionally, it evaluates the accuracy of the workout using angle thresholds. The system uses modules like numpy, Me- diaPipe, and cv2, with OpenCV handling images, MediaPipe handling multi-modal machine learning pipelines, and numpy handling angle computations and point management. With a high accuracy rate of 91 percent, this AI-based Vyayam model provides real-time feedback and finds applications in robotics, gaming, animation, movies, and physical therapy.

Based on the Shapley value, a cooperative game theory notion, Jianyuan Sun et al [12] introduced the Random Shapley Forests (RSFs) algorithm as a novel method for classification challenges. The Shapley value is used by RSFs to determine the feature importance of each tree node in a set of Shapley Decision Trees (SDTs). RSFs take into account the interde- pendence of characteristics, choosing those with low individual significance but high collective importance, in contrast to more conventional techniques like Random Forests (RFs). RSFs outperform RFs and other techniques in terms of classification accuracy across a range of datasets by using the Shapley value. Effective classification without overfitting is ensured by the algorithm's robust performance with respect to parameters such as the number of trees and randomly picked candidate characteristics.

The HuMAn system proposed by Pratool Bharti et al [13] is a sophisticated activity recognition system that categorizes different types of activities using information gathered from several body-worn sensors. The system is divided into three stages: multi-scale Conditional Random Field (CRF) classi- fication, data pre-processing and feature extraction, and final activity state classification that incorporates choices made by each wearable device. HuMAn resolves disparities in activ- ity classification among wearable devices by using a multi-positional decision selection strategy and CRF algorithms to take temporal correlations in activity sequences into account. In general, HuMAn uses contextual information and multi-modal sensor data to recognize complicated behaviors with greater accuracy.

Linsen Dong et al [14] presents two types of trainers that are intended to optimize settings for deep reinforcement learning (DRL) using Dyna-style models: the ensemble trainer and the unihead intelligent trainer. Using algorithms such as DQN, the unihead trainer learns both online and on-policy, but encounters difficulties in some cases because of associated actions and inadequate action quality assessment. On the other hand, the ensemble trainer incorporates several trainers with various policies to handle these problems. To improve performance, it makes use of weight transfer methods, order-based reward computation, memory sharing, and reference sampling. The ensemble trainer's adaptability and robustness are highlighted by experimental results showing that it delivers superior or comparable performance across a variety of tasks. Furthermore, computational cost studies demonstrate that the suggested trainers have a manageable overhead in comparison to conventional techniques, making them suitable for use in practical settings.

Bugra Tekin et al [15] endeavors to improve 3D posture es- timation from photos by merging two streams of information: one from recognizing 2D joint locations and another from studying the image directly. They combine these streams using various fusion algorithms to achieve the final 3D posture. They suggest a method for automatically learning how to combine these streams effectively. They also anticipate 2D joint posi- tions using a particular network design, which improves the overall accuracy of pose estimation.

Siddarth Sreeni et al [16] proposed posture recognition sys- tem collects data from numerous sensors, including a camera, an infrared sensor, and IMUs. It uses a 3D depth map and laser projection to calculate object distances, which are then mapped to construct a virtual skeleton. Two methods of posture recog- nition are used: one exhaustively compares gathered data to known postures, and the other employs machine learning with CNNs. The experimental results show appropriate posture prediction. The system collects data using a Kinect, an I2C multiplexer, BNO055 IMUs, and Teensy3.6 microcontrollers. Jiahua Xu et al. [17] describe a system for real-time hand gesture identification and motion tracking, which is suited for a variety of applications on conventional PCs equipped with web cams. It entails taking webcam frames, preprocessing them, and using a pre-trained Single Shot MultiBox Detector (SSD) for hand detection. A user-defined threshold confirms detections, which include bounding boxes and cropped hand images. Gesture identification uses a Convolutional Neural Network (CNN) trained on a proprietary dataset to recognize gestures from cropped hand photos. The motion tracking component uses hand centroid trajectories to derive directional gestures. This adaptable system has practical applications in real-time gesture detection and motion tracking, with the possibility for integration into other fields.

The creation of a posture assessment system that uses joint-specific feedback to guide yoga practitioners is covered by Ze Wu et al [18]. It suggests using quaternion data from wearable sensors as the basis for a Bayesian network model to assess body posture in relation to benchmark locations. The technology reduces errors and improves posture correctness by identifying nonstandard body components and offering recommendations for improvements. The system successfully directs practitioners to the proper postures with excellent recognition and evaluation accuracy. It also shows resilience to practitioner differences, which makes it a trustworthy instrument for assessing and advising on yoga posture.

Tewodros Legesse Munea et al [19] proposed process of identifying the single-person or multi-person poses of people in photographs. Both kinds of pose estimation have improved recently thanks to developments in deep learning and the availability of huge datasets like MPII and COCO. Top- down and bottom-up techniques are used, with ResNet being well-liked backbone designs. For training, loss functions such as Cross-Entropy, MSE, and MAE are utilized. COCO, MPII Human Pose, FLIC, and LSP are examples of common datasets. Performance is evaluated using parameters including PCP, PDJ, PCK, AUC, and OKS. Pose estimation techniques are continuously improved by developments in deep learning and non-linear systems.

The suggested system by Kang Wang et al. [20] introduces advanced body motions, eye gazing, and head attitude for human-computer interaction. It has a wide screen design and a variety of apps, such as a balloon shooting game and PowerPoint presentations. The system is an improvement over an earlier immersive system that prioritizes vision-based interaction over speaking. It's notable for enabling fluid Power- Point presentations with body language and estimating human attention with posture and look.

II. Methodology

A. *Data Preparation:*

1) **Labeling and Annotation:** Annotate collected video clips with labels for correct and incorrect postures, repetition counts, and other relevant information.
2) **Data Augmentation:** Augment the dataset by introducing variations in lighting conditions, camera angles, and user demographics to ensure robustness.

B. *Preprocessing and Model Utilization:*

1) **Video Preprocessing:** Apply techniques like resizing, cropping, and frame extraction to prepare video data for analysis.
2) **Pose Estimation with MediaPipe:** Utilize the MediaPipe library to estimate key body joints and points in yoga poses, meditation postures, and exercise routines. Extract relevant keypoints for posture analysis.

C. *System Integration and Development:*

1) **Unified Application Development:** Develop a unified application that incorporates posture monitoring and guidance for gym exercises, yoga, and meditation postures.
2) **Feedback Mechanisms:** Implement real-time feedback mechanisms to provide users with guidance on posture alignment, balance, and breathing techniques.

D. *Software and Hardware Integration:*

1) **Development Environment:** Develop the application using suitable development environments like Jupyter notebook, Anaconda Navigator, or IDEs.
2) **Library Integration:** Integrate computer vision libraries such as OpenCV and MediaPipe for video analysis and pose estimation.
3) **Hardware Requirements:** Ensure compatibility with cameras or webcams for real-time video input.
4) P*ose Detection and Repetition Counting:*

5) **Pose Detection:** Utilize the MediaPipe Pose model to detect key body landmarks in real-time webcam video frames.
6) **Angle Calculation:** Calculate the angles between relevant body landmarks, particularly for the left and right hands.
7) **Repetition Counting:** Track the changes in angles to infer repetitions for exercises based on predefined criteria.

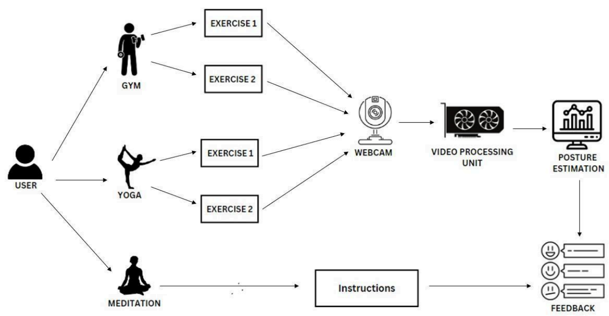

Fig. 1. Methodology Architecture

E. Web Application Development:

1) **Flask Integration:** Integrate the pose detection and repetition counting functionality into a Flask web application.
2) **HTML Rendering:** Render HTML templates for the home page and exercise view using Flask's render_template function.
3) **Video Stream Generation:** Implement a route to generate a video stream with real-time pose detection and repetition count overlay.

F. User Interaction:

1) **Exercise View:** Provide a dedicated route for users to view the exercise session with real-time feedback.
2) **Yoga and Meditation Routes:** Define routes for yoga and meditation options, enabling users to choose their preferred activity.
3) **Display Choices:** Display the user's chosen activity (e.g.," Yoga" or" Meditation") when accessing the respective routes.

G. Real-time Feedback and Visualization:

1) **Feedback Overlay:** Overlay real-time repetition counts for both hands on the video stream frame.
2) **Pose Landmark Visualization:** Draw pose landmarks on the video frame to provide visual feedback to the user.

H. Testing and Deployment:

1) **Testing:** Conduct extensive testing to ensure accurate pose detection, repetition counting, and user interaction.
2) **Deployment:** Deploy the Flask application for production use, ensuring stability and performance under varying conditions.

I. Expected Outcomes:

1) **Real-time Posture Monitoring:** Provide users with real- time feedback on their exercise performance, including posture correctness and repetition count.
2) **Enhanced User Engagement:** Improve user engagement and motivation by offering visual feedback and interactivity through the web application.
3) **Convenient Access:** Enable users to access exercise, yoga, and meditation guidance conveniently through a web browser from any device with a webcam.

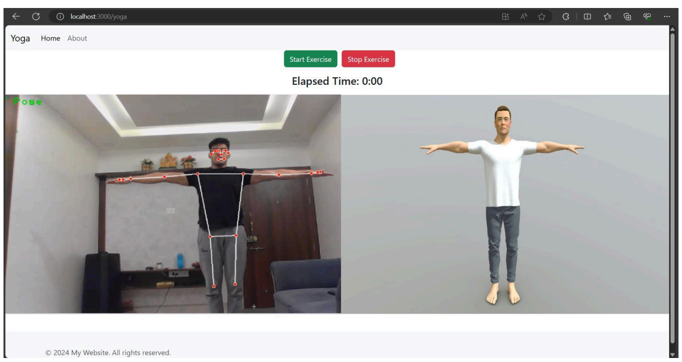

Fig. 2. Yoga Pose Detection

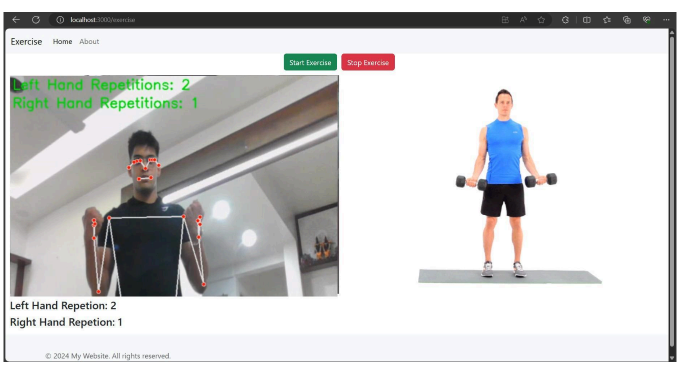

Fig. 3. Bicep Exercise

III. Algorithm and Analysis

Algorithm Analysis

Time Complexity: The overall time complexity is dominated by the continuous monitoring of angles, making it **O(n)**, where n is the number of frames processed during the exercise.

Space Complexity: The space complexity is influenced by the storage requirements of the pose estimation model, landmarks, calculated angles, and additional data related to angle changes over time. Assuming the dominant factor is the

Algorithm 1 Algorithm for Posture Monitoring and Yoga Pose Recognition with Flask

Require: Web application with Flask, OpenCV, and MediaPipe installed.
Ensure: Real-time video stream with posture monitoring and yoga pose recognition.

Step 1: Initialize Flask application.
Step 2: Define routes for endpoints
Step 3: Define function to calculate angle between landmarks.
Step 4: Define function to generate frames from webcam feed.
Step 5: Initialize MediaPipe Pose model.
Step 6: Open video capture device (webcam).
Step 7: Initialize variables for repetition counting and angle tracking.
Step 8: Start an loop to continuously process frames.
Step 8.1: Read frame from webcam.
Step 8.2: Resize frame to desired output resolution.
Step 8.3: Convert frame to RGB format.
Step 8.4: Process pose estimation on the frame. **Step 8.5:** Extract landmarks for left and right hands. **Step 8.6:** Calculate angles for left and right hands. **Step 8.7:** Interpolate angles to percentage scale.
Step 8.8: Update repetition counts based on angle changes.
Step 8.9: Draw pose landmarks on the frame.
Step 8.10: Display repetition counts on the frame.
Step 8.11: Encode frame as JPEG and yield as response.
Step 9: Release video capture device and stop Flask application when done.

continuous monitoring of angles, the space complexity is **O(1)**, indicating constant space requirements.

IV. Conclusion and Future Scope

A. Conclusion:

With its Artificial Intelligence and Machine Learning capabilities, the Pose-Craft Navigator is a powerful and novel tool for optimizing yoga poses in real time. This project makes use of contemporary technology, such as Computer Vision and Deep Learning, with an emphasis on libraries like MediaPipe and OpenCV. The algorithmic architecture of the research provides a systematic framework for frame preprocessing, landmark recognition, angle computation, and repetition counting, integrating Deep Learning and Flask for heightened precision in exercise monitoring. Posing flexibility in a range of yoga poses and workouts, together with an intuitive UI and extensive progress tracking capabilities, the Pose-Craft Navigator is an appealing tool for anybody looking for a comprehensive approach to fitness. This AI-powered solution demonstrates the revolutionary influence on improv- ing exercise routines, guaranteeing good form, and promoting general well-being as the field of fitness technology evolves.

Prospective endeavors could investigate supplementary modalities, optimize algorithms for improved precision, and broaden the system's compatibility with emerging technology. This dedication to continual research helps to advance the field of artificial intelligence and fitness, establishing the Pose-Craft Navigator at the vanguard of a new era of individualized, tech- enabled well-being.

B. Future Work:

1. Artificial Intelligence Coaching: Evolving the AI capabilities to act as a more personalized and intuitive virtual coach, offering real-time feedback, adaptive coaching strategies, and dynamic adjustments based on the user's performance, progress, and feedback.
2. Continuous Biomechanical Feedback: Enhancing the real- time feedback system to provide continuous biomechanical insights during workouts could assist users in refining their movements, preventing injuries, and optimizing their exercise routines for better long-term results.
3. Virtual Reality (VR) Integration: Exploring the integration of virtual reality experiences could offer users an immersive and engaging workout environment. Virtual landscapes, trainers, or interactive scenarios could enhance the overall fitness experience, making it more enjoyable and dynamic.
4. Wearable Device Integration: Integrating with wearable devices, such as smartwatches or fitness trackers, could provide users with seamless data synchronization, allowing for a more comprehensive analysis of their overall health and fitness metrics.
5. Accessibility Features: Ensuring the app is accessible to a diverse range of users by incorporating features like voice-guided instructions, customizable interfaces for different abilities, and compatibility with screen readers to promote inclusivity and cater to a broader audience.

References

[1] Hao-Shu Fang, Jiefeng Li, Hongyang Tang, Chao Xu, Haoyi Zhu, Yuliang Xiu, Yong-Lu Li, and Cewu Lu, "Alpha Pose: Whole-Body Regional Multi-Person Pose Estimation and Tracking in Real-Time" IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 45, no. 6, 2023, Publisher: IEEE.

[2] Keze Wang, Liang Lin, Pengxu Wei, Chen Qian, and Chenhan Jiang, "3D Human Pose Machines with Self-supervised Learning" IEEE Transactions on Industrial Informatics, vol. 15, no. 4, 2019, Publisher: IEEE.

[3] Hustinawaty, Tavipia Rumambi, Matrissya Hermita," Motion Detection Application to Measure Straight Leg Raise ROM Using MediaPipe Pose" 2022 4th International Conference on Cybernetics and Intelligent

System (ICORIS), 2022, Publisher: IEEE.

[4] Venkata Sai P. Bhamidipati, Ishi Saxena, Mrs. D. Saisanthiya, Dr. Mervin Retnadhas," Robust Intelligent Posture Estimation for an AI Gym Trainer using Mediapipe and OpenCV" 2023 International Conference on Networking and Communications (ICNWC), 2023, Publisher: IEEE.

[5] Tong Zhang, Jingxiang Lian, Jingtao Wen, and C. L. Philip Chen," Multi-Person Pose Estimation in the Wild: Using Adversarial Method to Train a Top-Down Pose Estimation Network" IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 53, no. 7, 2023, Publisher: IEEE.

[6] Filippos Markolefa, Konstantia Moirogiorgou, George Giakos, Michalis Zervakis," Virtual Video Synthesis for Personalized Training" 2018 IEEE International Conference on Imaging Systems and Techniques (IST), 2018, Publisher: IEEE.

[7] Nachaat Mohamed," Importance of Artificial Intelligence in Neural Network through using MediaPipe" Proceedings of the Sixth International Conference on Electronics, Communication and Aerospace Technology (ICECA 2022), 2022, Publisher: IEEE.

[8] Rohit Girdhar, Georgia Gkioxari, Lorenzo Torresani, Manohar Paluri, and Du Tran," Detect-and-Track: Efficient Pose Estimation in Videos" IEEE Conference on Computer Vision and Pattern Recognition, 2018.

[9] Ashish Gupta and Hari Prabhat Gupt, "YogaHelp: Leveraging Motion Sensors for Learning Correct Execution of Yoga With Feedback" IEEE Transactions on Artificial Intelligence, vol. 2, no. 4, 2021, Publisher: IEEE.

[10] Bruce Xiaohan Nie, Ping Wei, and Song-Chun Zhu," Monocular 3D Hu- man Pose Estimation by Predicting Depth on Joints" IEEE International Conference on Computer Vision, 2017, Publisher: IEEE.

[11] Samhitha G, Srinivasa Rao D, Ch. Rupa, Y. Ekshita, and R Jaswanti, "Vyayam: Artificial Intelligence based Bicep Curl Workout Tracking System" 2021 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES), 2021, Publisher: IEEE.

[12] Jianyuan Sun, Hui Yu, Guoqiang Zhong, Junyu Dong, Shu Zhang, and Hongchuan Yu," Random Shapley Forests: Cooperative Game-Based Random Forests with Consistency" IEEE Transactions on Cybernetics, 2020, Publisher: IEEE.

[13] Pratool Bharti, Debraj De, Sriram Chellappan, and Sajal K. Das," HuMAn: Complex Activity Recognition with Multi-modal Multi-positional Body Sensing" IEEE Transactions on Mobile Computing, vol. 18, 2019, Publisher: IEEE.

[14] Linsen Dong, Yuanlong Li, Xin Zhou, Yonggang Wen, and Kyle Guan," Intelligent Trainer for Dyna-Style Model-Based Deep Reinforcement Learning," IEEE Transactions on Neural Networks and Learning Systems, 2020, Publisher: IEEE.

[15] Bugra Tekin, Pablo Marquez-Neila, Mathieu Salzmann, Pascal Fua," Learning to Fuse 2D to 3D Image Cues for Monocular Body Pose Estimation" 2017 IEEE International Conference on Computer Vision, 2017, Publisher: IEEE.

[16] Siddarth Sreeni, Hari S R, Harikrishnan R, and Sreejith V," Multi-Modal Posture Recognition System for Healthcare Applications" Proceedings of TENCON 2018 - 2018 IEEE Region 10 Conference, 2018, Publisher: IEEE.

[17] Jiahua Xu, Priyanka Mohan, Faxing Chen, and Andreas Nu¨rnberger," A Real-time Hand Motion Detection System for Unsupervised Home Training" IEEE International Conference on Systems Man and Cybernetics, 2020, Publisher: IEEE.

[18] Ze Wu, Jiwen Zhang, Ken Chen, and Chenglong Fu," Yoga Posture Recognition and Quantitative Evaluation with Wearable Sensors Based on Two-Stage Classifier and Prior Bayesian Network" Sensors 2019, 19, 5129, Publisher: Sensors.

[19] Tewodros Legesse Munea, Yalew Zelalem Jembre, Halefom Tekle Weldegebriel, Longbiao Chen, Chenxi Huang, and Chenhui Yang," The Progress of Human Pose Estimation: A Survey and Taxonomy of Models Applied in 2D Human Pose Estimation" Preparation of Papers for IEEE Access, 2017, Publisher: IEEE.

[20] Kang Wang, Rui Zhao and Qiang Ji" Human Computer Interaction with Head Pose, Eye Gaze and Body Gestures" 13th IEEE International Con- ference on Automatic Face and Gesture Recognition 2018, Publisher: IEEE.