



Yoga pose recognition and motion analysis for a home-based fitness monitoring and health management system

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Abstract

This study explores AI applications in motion recognition, focusing on the development of a home-based fitness monitoring and health management system that eliminates the need for a gym. By integrating dynamic exercises (e.g., Knee Lifts, Bicep Curls) with static yoga poses (e.g., Tree Pose, T-pose, Warrior Pose), the system provides real-time feedback to enhance workout effectiveness and overall health outcomes. OpenPose-based keypoint detection enables precise pose analysis, supporting personalized fitness plans tailored to individual users. A scoring system quantifies pose accuracy, ensuring proper form and minimizing injury risk. The implementation of OpenPose's predictive model has yielded promising results, achieving a prediction accuracy of 99.9%. This system serves as a foundational step toward automated image and video analysis for both dynamic exercises and static yoga poses, making personalized fitness training more accessible and effective in home environments.

Keywords OpenPose · Dynamic Poses · Yoga · Personalized Exercise Plans · Scoring System

1 Introduction

1.1 Background and motivation

The rise of artificial intelligence (AI) in fitness and health monitoring highlights its potential to improve the well-being of older adults [1]. Regular physical activity is crucial for maintaining health, especially among older adults [2]. Differences in biomechanics and physical function of stair descent in older adults [3]. Prevent Falls in the Elderly [4]. By emphasizing the connection between physical activity and cognitive health, this study contributes to the development of evidence-based recommendations that benefit individuals across all age groups, ultimately enhancing overall health and well-being [5]. Physical activity (PA) is considered a nonpharmacological strategy for preventing cognitive decline [6]. Practicing yoga [7] at home allows individuals to

maintain physical and mental well-being without the need for specialized equipment or access to fitness centers, making it an accessible option for many.

Yoga [8], known for enhancing physical and mental health, serves as an ideal case study for AI-driven motion analysis. However, accurate and real-time yoga posture recognition, particularly for older individuals, remains a challenge.

OpenPose [9], a state-of-the-art pose estimation framework, enables real-time analysis of joint positions, providing a foundation for intelligent movement assessment. While OpenPose excels in detecting human skeletal structures, existing yoga pose recognition systems struggle with real-world variations, such as pose asymmetry, variations in execution styles, and movement transitions. Furthermore, most conventional AI-based pose recognition models focus on athletic populations, overlooking the distinct biomechanical characteristics and safety considerations for older adults.

To bridge this gap, we propose an OpenPose-based yoga pose recognition system designed specifically for older adults. Our system not only detects static and dynamic poses but also integrates real-time feedback mechanisms, ensuring safety and accuracy.

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1.2 Research gap and uniqueness

Despite advancements in AI-driven pose recognition, existing systems exhibit several limitations:

Limited Focus on Older Adults: Most pose recognition models are optimized for young and athletic users, leading to reduced accuracy when applied to older adults due to differences in flexibility, balance, and execution speed.

Challenges in Static and Dynamic Pose Recognition: Current models either focus exclusively on static yoga poses or general fitness movements, making them inadequate for recognizing a combination of dynamic transitions and sustained postures.

Lack of Real-time Feedback for Safety: Many existing systems analyze recorded data but fail to provide immediate corrections, which are critical for preventing injuries and improving training effectiveness.

Pose Ambiguity and Asymmetry Issues: Traditional machine learning models often misclassify poses due to asymmetrical limb positions or non-standardized execution styles, which are common among older practitioners.

To address these gaps, our proposed system introduces:

Enhanced static and dynamic pose detection tailored to older adults. A real-time feedback mechanism to provide immediate corrections. A novel scoring algorithm that accounts for asymmetry and gradual movement transitions, ensuring higher accuracy. Seamless integration into digital health platforms to enable long-term monitoring and personalized recommendations.

1.3 Contribution

This study proposes a home-based fitness monitoring and health management system utilizing OpenPose for accurate yoga pose and motion recognition. The major contributions are:

- Accurate recognition of dynamic movements (e.g., Knee Lifts, Bicep Curls) and static yoga poses (e.g., Tree Pose, T-pose, Warrior Pose) adapted for older adults.
- Real-time feedback to correct postures, enhancing exercise safety and effectiveness.
- Seamless integration into digital health platforms for personalized, long-term health monitoring.
- Enhanced recognition algorithm addressing pose asymmetry and motion variation to reduce misclassification.
- Support for user-defined pose registration, enabling system adaptability to new exercises.
- Joint angle-based classification and scoring for detailed movement quality assessment.

- High recognition accuracy (up to 99.9%) achieved by combining OpenPose keypoints and rule-based evaluation, ensuring reliable home-based use.

These innovations contribute to AI-driven health technology, offering a scalable and accessible solution for personalized fitness and well-being management at home.

2 Related work

2.1 OpenPose in motion recognition

OpenPose is a state-of-the-art tool for pose estimation, capable of extracting 2D skeletal keypoints [10] from video frames. Its applications span fitness tracking, rehabilitation, and sports analysis. However, leveraging OpenPose for yoga pose recognition, especially for older adults, requires additional customization. This includes integrating joint angle computations and developing algorithms to analyze pose symmetry and stability.

Research shows that using keypoint data from OpenPose to compute joint angles can significantly improve pose classification accuracy. Previous studies, such as [11], demonstrated the use of OpenPose for analyzing gait and movement symmetry, but limited research focuses on static and dynamic yoga poses.

2.2 Angle-based pose analysis

Angle-based methods are particularly effective in yoga pose recognition. By calculating the relative angles between keypoints, systems can differentiate subtle variations in postures. For example, the angle formed by the hip, knee, and ankle is crucial for distinguishing poses like Tree Pose and Warrior Pose. Existing systems often rely on manual feature engineering or less robust estimation techniques, which lack the precision offered by OpenPose's keypoint extraction, as shown in Figure 1 and Figure 2.

This study extends the use of OpenPose by introducing angle-difference calculations to compare user poses against reference poses. This approach enhances recognition by accounting for variations such as left- or right-sided postures, addressing challenges like misclassification of Warrior Pose as Tree Pose when leg configurations differ.

2.3 Yoga and home-based fitness

Yoga has gained widespread popularity as a convenient and effective home-based fitness practice. Research highlights its benefits in improving flexibility, posture, balance, and mental wellness across all age groups. However, many digital fitness

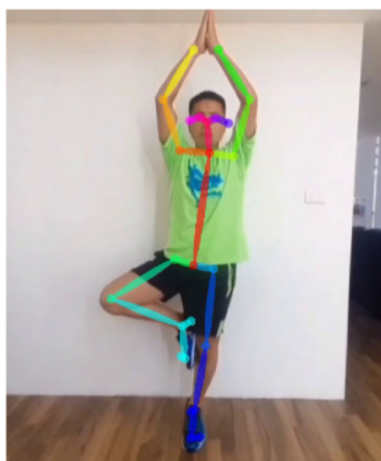


Fig. 1 yoga tree pose detected by OpenPose

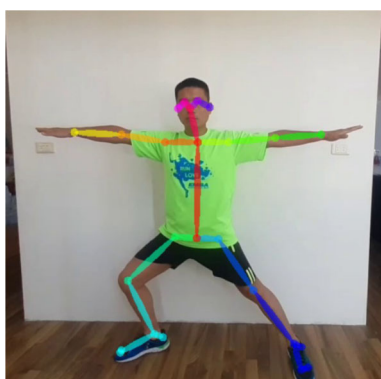


Fig. 2 yoga warrior pose detected by OpenPose

systems remain generalized and are not optimized for users who prefer exercising at home without access to a gym.

This study addresses that gap by developing a system that supports both static yoga poses and dynamic exercises using OpenPose for accurate keypoint extraction. The angle-based analysis enables personalized feedback, making it suitable for users of various ages and physical conditions who engage in fitness routines in a home environment.

Moreover, by combining OpenPose with angle-based analysis, the proposed system offers a scalable and adaptable solution for monitoring and guiding yoga practice. It evaluates joint angles in real time, enabling users to receive immediate feedback on their posture accuracy and movement consistency. This integration not only supports individual exercise tracking but also facilitates self-guided correction without requiring in-person supervision.

Such a framework is particularly valuable in home settings, where users may lack access to professional trainers. The system empowers individuals to maintain proper form, improve exercise efficiency, and reduce injury risks-making it a reliable tool for both beginners and experienced practitioners engaging in yoga or fitness training at home.

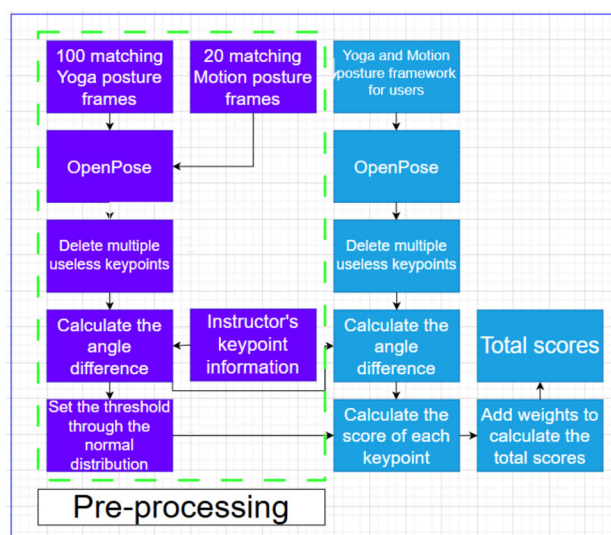
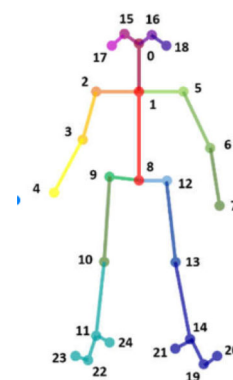


Fig. 3 Proposed system architecture

Fig. 4 Skeleton information of the human body by OpenPose



3 Methodology

3.1 System design

The system architecture of the proposed design is depicted in Figure 3. We selected 3 Yoga postures for the experiments, which include “Tree Pose”, “T-pose”, “Warrior Pose”, and 2 Motion postures for the experiments, which include “Knee Lifts”, and “Bicep Curls”. By the pre-processing process, each Yoga posture has its own properties, i.e. the selected keypoints and the corresponding weights.

The system uses OpenPose to extract skeletal keypoints, as shown in Figure 4[12], which are processed to identify pose characteristics. A rule-based algorithm complements OpenPose outputs for dynamic and static pose classification.

3.2 Data collection and preprocessing

- **Dataset:** Videos of adults performing five exercises (two dynamic and three static poses), specifically designed for use in home environments.
- **Preprocessing:**

- **Video Standardization:** All input videos are converted to a uniform resolution (e.g., 640×480) and frame rate (e.g., 30 FPS) to ensure consistency during analysis.
- **Frame Sampling:** Videos are segmented into individual frames using fixed intervals (e.g., every 5th frame) to balance computational load and temporal resolution.
- **Region of Interest (ROI):** Only the relevant portion of each frame is retained based on expected user positioning, reducing background noise and improving pose estimation.
- **Keypoint Extraction:** OpenPose generates a 25-point skeletal model for each frame, covering major joints such as shoulders, elbows, knees, and ankles.
- **Normalization:** Extracted keypoints are normalized with respect to torso size or body height to ensure scale invariance and accommodate different user body proportions.
- **Noise Removal:** Missing or low-confidence keypoints are interpolated or excluded to reduce noise in angle calculations and improve recognition stability.
- **Augmentation:** To improve generalization, variations in brightness, orientation, and camera angle are synthetically introduced to simulate real-world recording conditions.

3.3 Pose classification

3.3.1 Static pose analysis:

Static pose classification relies on joint angle comparisons derived from OpenPose outputs, as shown in Figure 5. Keypoints such as the hips, knees, ankles, and shoulders are analyzed to verify posture accuracy.

For Tree Pose, the system:

- **Assesses hip-knee-ankle angles** using keypoints [9-10-11] (right leg) and [12-13-14] (left leg) to determine the lifted leg position.
- **Evaluates shoulder alignment** via keypoints 2 (R-Shoulder) and 5 (L-Shoulder) to ensure upper body stability.
- **Measures spine inclination** from the mid-hip (average of keypoints 9 and 12) to neck (keypoint 1) to assess balance.

This method enables accurate static pose recognition even with minor limb variations, leveraging OpenPose's 25-joint skeleton model.

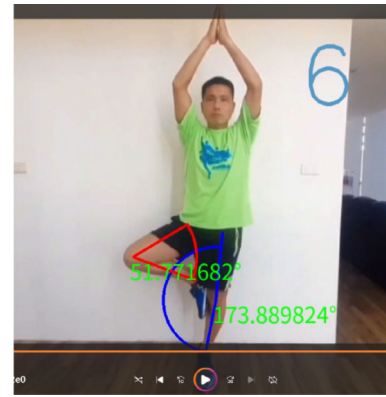


Fig. 5 Static Pose -Yoga Tree Pose.

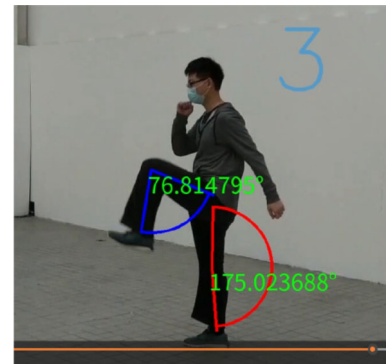


Fig. 6 Dynamic Action Tracking

3.3.2 Dynamic action tracking:

Dynamic movement analysis focuses on tracking time-series variations in keypoints, as illustrated in Figure 6.

For Knee Lifts, the system:

- **Monitors hip-knee-ankle angles** from keypoints [9-10-11] and [12-13-14] to measure knee elevation quality.
- **Counts repetitions** by detecting cycles where the knee height surpasses a defined threshold.
- **Evaluates movement smoothness** by analyzing angular velocity for controlled versus erratic execution.

Dynamic Time Warping (DTW) [13] aligns user movements with ideal trajectories, improving the precision of motion recognition and feedback generation.

3.4 Scoring system

In this study, a statistical-based scoring system was developed to evaluate the quality of users' dynamic (e.g., Knee Lifts, Bicep Curls) and static yoga poses (e.g., Tree Pose, T-pose, Warrior Pose). The system operates through the following steps:

3.4.1 Keypoint selection

Keypoints relevant to both dynamic and static yoga poses (e.g., shoulders, knees, hips, wrists, and ankles) are selected from the 25 skeletal keypoints extracted by OpenPose for detailed analysis.

3.4.2 Angle and distance calculation

For static poses (e.g., Tree Pose, T-pose, Warrior Pose), joint angles are computed and compared to reference pose values. A deviation-based scoring mechanism evaluates how closely the user's posture aligns with the ideal pose.

For dynamic actions (e.g., Knee Lifts, Bicep Curls), temporal variations in joint positions are analyzed to ensure smooth and consistent movements. Key parameters include:

- **Smoothness:** Sudden jerky movements negatively impact scores.
- **Range of Motion:** The extent of joint displacement is compared to reference values.
- **Alignment Over Time:** The trajectory of joint movements is assessed.

3.4.3 Dynamic time warping (DTW) for motion comparison

To evaluate dynamic actions, we employ Dynamic Time Warping (DTW), a widely used algorithm for measuring similarities between time-series data. DTW aligns the user's joint trajectories with reference movement patterns by handling variations in execution speed. This ensures that the system can accurately compare movements even if users perform them at different speeds.

3.4.4 Distance-based evaluation

For distance-based verification, we measure the Euclidean distance between keypoints across frames. This method helps analyze movement stability and ensure that users maintain proper form throughout dynamic exercises.

By integrating angle deviation analysis, DTW-based time-series comparison, and Euclidean distance evaluation, our system ensures a comprehensive assessment of both static and dynamic poses.

3.4.5 Score calculation

Static Poses: A local score is calculated for each keypoint by measuring the deviation of its angle from the reference pose values. The smaller the deviation, the higher the score (maximum: 100 points).

Table 1 Feedback Levels Based on Score Intervals

Score Range	Feedback Level
0–20	Bad
21–40	Slightly bad
41–60	Normal
61–75	Good
76–100	Very good

Dynamic Actions: Scores are calculated based on the smoothness, range of motion, and alignment of movements over time. The following formula applies to both cases:

$$\text{Score}_i = 100 - \left| \frac{\text{Observed Value}_i - \text{Reference Value}_i}{\text{Reference Value}_i} \right| \times 100 \quad (1)$$

where i represents the index of the keypoint or joint being evaluated. Each joint is assigned a score based on its deviation from the reference value, contributing to the overall posture assessment.

3.4.6 Weighted total score

Each keypoint is assigned a weight based on its importance to the overall pose or movement. The total score is computed using the formula:

$$\text{Total Score} = \sum_{i=1}^n \text{Weight}_i \times \text{Score}_i \quad (2)$$

where n is the number of selected keypoints.

3.4.7 Output results

The final score is divided into a feedback scale, as illustrated in Figure 7. As shown in Table 1, this scoring system provides users with actionable insights based on their performance.

This scoring system provides dynamic and static yoga pose practitioners with tailored feedback, helping them refine their movements and poses while minimizing the risk of injury.

3.4.8 Rationale for the scoring system

The scoring scale is inspired by established motion evaluation frameworks used in physical therapy and sports science. By mapping joint deviations and movement consistency to a five-tier feedback system, users receive intuitive and structured guidance. This approach aligns with methodologies

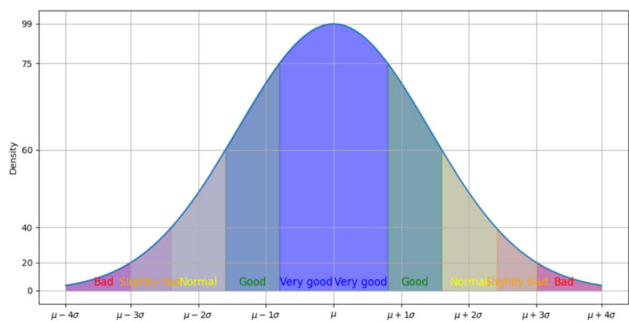


Fig. 7 The interval of posture evaluation at the selected keypoint.

found in pose estimation research and rehabilitation assessment studies.

3.4.9 Figure source

Figure 7 is derived from our experimental data analysis. The score intervals are determined based on statistical variations in joint angles across multiple trials of correct and incorrect postures. This ensures that the feedback categories align with real-world deviations observed during yoga and fitness training sessions.

3.5 User interface and interaction flow

To support home-based fitness monitoring, the system offers a streamlined web-based interface, as shown in Figure 8. The main components include:

- **Action Selection:** Users select yoga poses or dynamic movements (e.g., YOGA_TREE, YOGA_WARRIOR, Knee Lifts) from a drop-down list. New static and dynamic actions can also be registered for future evaluations.
- **Video Upload:** Users upload videos for analysis, with filenames displayed for confirmation.
- **Demographic Input:** Users input gender and age, allowing personalized threshold adjustments.
- **Submit and Analysis:** The system processes videos with OpenPose, evaluates joint angles, classifies poses, and provides performance scores.
- **High Accuracy:** Combining keypoint-based analysis and rule-based logic, the system achieves up to 99.9% recognition accuracy.

Designed for older adults and non-technical users, the system runs efficiently on embedded platforms like NVIDIA Jetson Nano, enabling accessible home-based fitness evaluation.

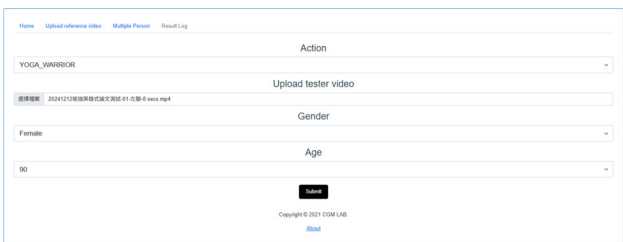


Fig. 8 System interface for home-based yoga pose recognition and evaluation.

Table 2 Recognition Accuracy and System Performance

Pose type	Accuracy (%)
Tree Pose (Static)	99.9
T-pose (Static)	99.9
Warrior Pose (Static)	99.9
Knee Lifts (Dynamic)	99.0
Bicep Curls (Dynamic)	99.0
System performance	Achieved consistent 99.9% accuracy in static poses across multiple subjects.
Misclassification reduction	Improved Warrior Pose accuracy by refining detection rules for left and right leg positions.

4 Results and discussion

4.1 Accuracy and performance metrics

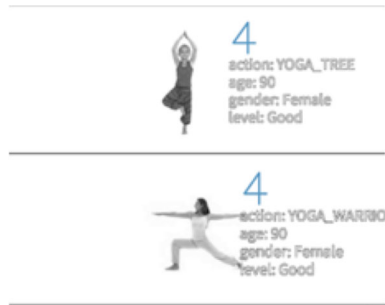
The system demonstrates high reliability in static yoga pose recognition, achieving a consistent 99.9% accuracy. For dynamic actions such as Knee Lifts and Bicep Curls, recognition accuracy reached 99.0%, which, while slightly lower than static poses, still demonstrates strong performance in real-world conditions. These values were validated across multiple trials using different participants, environments, and lighting conditions to ensure robustness and reproducibility.

As shown in Table 2, the system accurately identifies both static and dynamic movements. This includes precise classification of Tree Pose, T-pose, and Warrior Pose, as well as dynamic actions involving leg and arm movement. The Warrior Pose classification was particularly improved by refining rules related to distinguishing between left and right leg stances.

This high level of accuracy illustrates the robustness and reliability of the proposed system in real-time motion recognition, especially when applied to older adults in home-based environments. Experimental results show the system’s strong potential for deployment in personalized fitness applications.

Table 3 Accuracy Comparison

Model	Accuracy (%)
HoG	70.3%
Hu Moment	73.5%
CNN	68.3%
Transfer Learning	85%
Our System	99.9%

**Fig. 9** Prediction results for yoga pose test videos (from top to bottom): YOGA_TREE and YOGA_WARRIOR achieved a LEVEL of good results.

4.2 Transfer learning performance vs our system performance

Table 3 shows the accuracy for Transfer Learning architectures alongside our system to solve the mentioned classification problem with the mentioned data.

In [14] studies reported an accuracy range between 68.3% (CNN) and 85% (Transfer Learning). In contrast, our system achieves a consistent 99.9% accuracy, significantly surpassing the highest accuracy reported in the referenced study. This comparison highlights the advanced capabilities of our system in static yoga pose recognition, as shown in Figure 9.

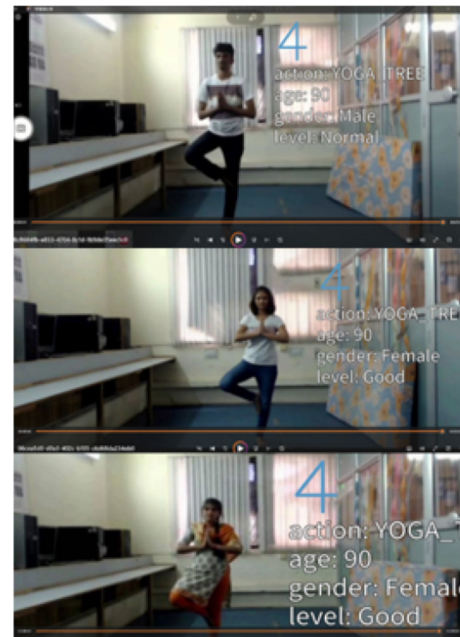
Figure 9 presents the prediction results of the trained model on test videos of different yoga poses, demonstrating high-confidence classification of yoga postures.

4.3 State-of-the-art performance v.s. our system performance

Table 4 shows the accuracy for State-of-the-Art architectures alongside our system to solve the mentioned classification problem with the mentioned data. In [15] studies reported demonstrated competitive results, with the Hybrid CNN & LSTM and 3DCNN Model1 achieving the highest accuracy of 99.65%. However, our system outperforms all models, achieving both an average and highest accuracy of 99.9%, demonstrating superior consistency and robustness. This comparison highlights the advanced capabilities of our system in static yoga pose recognition.

Table 4 Accuracy Comparison

Model	Average Recognition Accuracy (%)	Highest Recognition Accuracy (%)
Hybrid CNN & LSTM	98.80	99.65
3DCNN Model1	99.07	99.65
3DCNN Model2	98.19	99.38
3DCNN Model3	98.43	99.38
Our System	99.90	99.90

**Fig. 10** Prediction results for yoga pose test videos: YOGA_TREE achieved a LEVEL of good results.**Table 5** Accuracy Comparison

Architecture	Accuracy (%)
YoNet	95.61
Our System	99.90

Figure 10 presents the prediction results of the trained model on test videos of different yoga poses, demonstrating high-confidence classification of yoga postures.

4.4 YoNet performance vs our system performance

Table 5 shows the accuracy for YoNet architectures alongside our system to solve the mentioned classification problem with the mentioned data. In [16] studies reported an accuracy of 95.61% using its neural network architecture. While impressive, our system achieves a significantly higher accuracy of 99.9%, highlighting its advanced capabilities in yoga pose

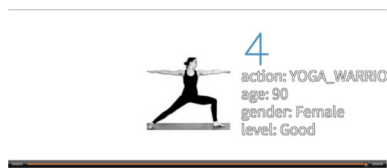


Fig. 11 Prediction results for yoga pose test videos: YOGA_WARRIOR achieved a LEVEL of good results.

recognition. The robustness and precision of our approach demonstrate its potential to set new standards in real-time yoga pose classification.

These comparisons with prior studies [14, 15], and [16] underscore the superior performance of our system. With a consistent accuracy of 99.9% for static poses and notable improvements in dynamic action recognition, our system sets a new benchmark in the field of yoga pose recognition. Its exceptional precision and real-time capabilities make it a valuable tool for health monitoring and personalized fitness applications.

This comparison highlights the advanced capabilities of our system in static yoga pose recognition, as shown in Figure 11.

Figure 11 presents the prediction results of the trained model on test videos of different yoga poses, demonstrating high-confidence classification of yoga postures.

5 Experiment and discussion

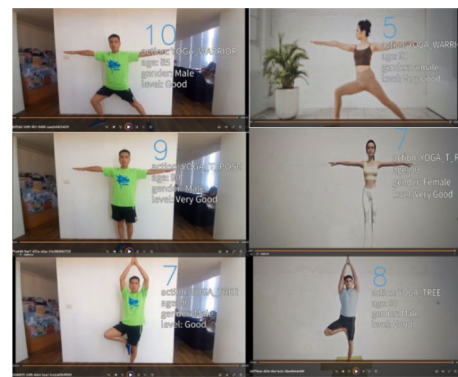
5.1 Experiment

The system was implemented on an NVIDIA Jetson Nano. The webcam was positioned at 95 cm height and 330 cm distance. To optimize performance, only the region of interest (ROI) was processed. Pose evaluation was tailored based on the user's action, gender, and age.

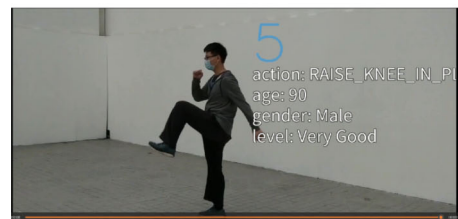
Dynamic exercises were scored based on the number of correct repetitions, while static poses were scored by the duration (in seconds) of correct posture. Experimental results, shown in Figure 12, confirmed the system's effectiveness in real-time posture evaluation.

5.2 Discussion and limitations

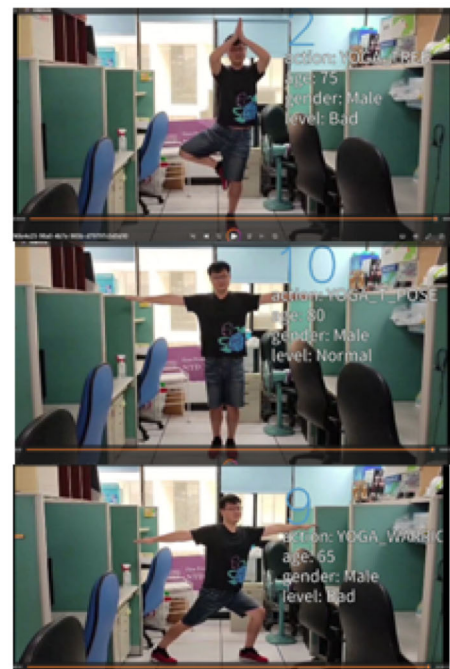
Although the proposed system achieves high accuracy for static yoga poses, its performance on dynamic actions is influenced by factors such as inconsistent movement execution, background variation, and camera angle. The current implementation is also limited by the size and diversity of the test dataset. Additionally, feedback is currently rule-based and not yet adapted through learning user-specific behavior.



(a)



(b)



(c)

Fig. 12 Experimental results of the “Yoga” and “Motion” posture. (a) Experimental result for a good posture. (b) Experimental result for a good posture. (c) Experimental result for a bad posture

6 Conclusion and future work

This study proposes a home-based motion recognition system using OpenPose that delivers high-accuracy results for both static and dynamic yoga poses. While the system performs exceptionally for static postures, dynamic actions still present challenges due to inter-subject variability and motion blur. Future improvements may include integrating wearable inertial sensors and expanding training data to enhance robustness.

Author Contributions Conceptualization: San-Chi Yeh; Methodology: San-Chi Yeh; Formal analysis and investigation: San-Chi Yeh; Writing - original draft preparation: San-Chi Yeh; Writing - review and editing: San-Chi Yeh, Chuan-Kai Yang; Resources: Chuan-Kai Yang; Supervision: Chuan-Kai Yang. All authors have read and agreed to the final version of the manuscript.

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Data Availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests The authors declare that they have no conflict of interest.

Ethics approval Since the data used for this research does not involve human or animal participants, this section is not applicable.

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