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Original Article

QUANTITATIVE EVALUATION OF YOGA POSTURES USING IMAGE PROCESSING AND HOTELLING'S T^2 STATISTICAL ANALYSIS

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ABSTRACT

The aim of this study is to use computer vision and statistical analysis to measure how yoga practice can improve body posture. A Python-based model was developed that can recognize different yoga poses from images and then create a 3D skeleton of the human body using landmark points. For each pose, twelve important landmarks such as shoulders, elbows, hips, and knees were identified, and angles were calculated to check the correctness of posture. To evaluate whether these landmarks showed improvement after one month of yoga practice, we applied Hotelling's T^2 test, a multivariate statistical method that can detect overall changes across several joints at the same time. The results showed that some landmarks had significant differences before and after yoga, meaning that the posture became more aligned and balanced. This method provides an objective way of checking yoga progress instead of relying only on visual observation. The study demonstrates that by combining image processing with statistical testing, it is possible to give meaningful feedback to yoga practitioners, trainers, and even rehabilitation experts in a simple and scientific manner

Keywords: Yoga Posture Analysis, Image Processing, Computer Vision, 3D Skeleton Model, Landmark Detection, Hotelling's T^2 Test

INTRODUCTION

Yoga encompasses a broad spectrum of practices, from physical postures (asanas) and breathing techniques (pranayama) to meditation and ethical living. Ancient texts such as the Bhagavad Gita and Patanjali's Yoga Sutras emphasize yoga as both a practical discipline and a path to self-realization. In modern times, yoga's versatility enables adaptation for all ages and backgrounds—whether as a gentle means for injury rehabilitation, a dynamic tool for fitness, or a structured method to foster mindfulness. The surge in global popularity reflects its accessibility and multifaceted contributions to individual and societal health.

Scientific studies increasingly validate yoga's role in addressing major modern challenges, including stress, sedentary lifestyles, and rising chronic disease rates. Consistent practice cultivates physical flexibility and strength, supports heart health, and aids in metabolic balance. Breathwork and meditative elements foster nervous system resilience by reducing sympathetic (fight-or-flight) activity and enhancing parasympathetic (rest-and-digest) function, directly impacting stress reduction, sleep quality, and immune competence. Regular yoga sessions are linked with lower rates of hypertension, anxiety, depression, and chronic pain. Emerging research also highlights yoga's effect on improving neuroplasticity, attention, memory, and emotional regulation.

Despite decades of anecdotal and clinical evidence supporting yoga's efficacy, rigorous quantification—particularly of biomechanical improvements—remains under-explored. Recent studies leverage image processing and computer vision methods to

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objectively assess posture quality, symmetry, and improvements over time. These advancements are crucial for bridging the gap between traditional practice and evidence-based health promotion. Using tools like pose estimation algorithms and landmark tracking, researchers and practitioners can now gain precise, visual feedback on alignment and progress, providing tangible metrics for personalized guidance and large-scale studies.

Yoga's impact is not restricted to individual health. Group practices encourage social cohesion, foster supportive communities, and contribute to healthier workplaces and educational environments. Public health initiatives increasingly recognize yoga as a cost-effective, scalable intervention for enhancing population wellbeing and reducing healthcare burden, especially in contexts where access to conventional medical or psychological care may be limited.

Yoga continues to evolve as a dynamic interface between tradition and innovation, embodying both an ancient wisdom and a modern science of self-care and self-mastery.

STUDY OBJECTIVES

1) Develop a computer vision model to detect and classify yoga poses from static images using advanced landmark detection frameworks.
2) Apply Mediapipe for extracting 32 body landmarks per image to enable accurate mapping of joints and limbs for analysis.
3) Compute joint angles from landmark coordinates using the Pythagorean theorem and law of cosines, providing quantitative alignment measures.
4) Create rule-based algorithms that classify poses by mapping joint angles to benchmark ranges for automated recognition.
5) Overlay detected landmarks and pose labels onto images to visually validate algorithm results.
6) Evaluate classification and angle estimation accuracy through comparative analysis of before-and-after images, measuring improvements in alignment and posture.

LITERATURE REVIEW

Cramer et al. (2013) conducted a meta-analysis investigating yoga's effects on depression, demonstrating significant mental health benefits. Their broad literature screening supports yoga as a complementary therapy. Yet, variability in study designs, yoga styles, and intervention durations presents challenges for standardized conclusions, indicating a need for more uniform future trials.

Jain et al. (2015) used image processing and machine learning methods for yoga pose recognition, aiming to improve physical alignment through software-guided feedback. Their work laid foundational groundwork for later pose detection models. However, the study is constrained by limited computational resources and simpler machine learning methods of the time, which may reduce accuracy and robustness compared to recent deep learning-based approaches.

Li and Goldsmith (2015) reviewed the effects of yoga on anxiety and stress, consolidating clinical evidence that supports regular practice for mental well-being. They discuss neurobiological mechanisms behind benefits, but the review notes inconsistencies and methodological differences across individual studies, which compromise the overall strength of the evidence.

Wu et al. (2016) proposed a convolutional neural network (CNN) with transfer learning to recognize yoga poses automatically from images, achieving high classification accuracy in controlled datasets. The study's limitation lies in its assumption of clear backgrounds and static postures, which may not hold true in dynamic or real-world settings with occlusions or complex environments.

Raghavendra et al. (2019) explored the physical benefits of guided yoga intervention by employing yoga pose recognition techniques to monitor alignment improvements. The study also measured stress reduction outcomes, confirming yoga's efficacy. Limitations include a relatively small sample size and the use of predefined poses only, which could limit the applicability to practitioners performing more advanced or hybrid postures.

Kishore et al. (2022) conducted a comparative evaluation of four deep learning architectures—EpipolarPose, OpenPose, PoseNet, and MediaPipe—for yoga pose estimation. Using a database from the Swami Vivekananda Yoga Anusandhana Samsthana (S-VYASA), they concluded that MediaPipe achieved the highest accuracy in estimating five common postures. Their contribution includes benchmarking model performance for yoga-specific data. However, the training dataset covers only five asanas, which limits scalability to wider yoga practice diversity. Additionally, the system mainly relied on monocular input, which might not capture complex 3D posture nuances fully.

Shailesh and Jose (2022) implemented a deep learning framework for automatic yoga pose estimation and feedback generation. Their model integrates pose estimation with feedback mechanisms to suggest corrections. They highlight the utility of deep architectures in capturing intricate pose details. The system was tested on a curated dataset but lacks validation in uncontrolled or varied user environments. The challenge in generalizing model performance to different camera settings and body types remains a concern.

Madhavi, M., Shashank, V., Vaishnavi, R., and Abhinav, S. (2024) proposed a convolutional neural network (CNN)-based method for identification and correction of yoga poses using an image database of five common asanas. Their approach focuses on pose correction by detecting misalignments from captured images. The study demonstrates promising pose classification accuracy, yet it is limited to static images rather than continuous video streams, leaving temporal pose consistency and dynamic movement unaddressed. This confines the practical application in real-time yoga sessions where flow between poses matters.

Anusha et al. (2025) developed a system using machine learning for real-time yoga pose detection, leveraging the MediaPipe Blaze pose model coupled with an XGBoost classifier. Their system extracts key body points, classifies yoga poses, and provides real-time corrective feedback. This approach is designed to improve self-practice accuracy and remote instruction. While the model shows high accuracy, the study relies heavily on quality input images and does not extensively address performance variability across diverse user environments or lighting conditions, which may affect robustness in real-world scenarios.

DATA COLLECTION

This part of the study used still images of yoga postures taken before and after a one-month period of practice. Images came from two sources: (a) photographs of study participants who attended the yoga event, and (b) benchmark images collected from public datasets and online resources used to define correct pose angles. Images of the same participants were paired so that each person has a “before” and an “after” image for the same pose; these paired images were used for statistical comparison of landmarks.

IMAGES WERE OBTAINED FROM TWO PRIMARY SOURCES

Captured Images: Photographs were taken under consistent lighting and background conditions to minimize noise and ensure accurate detection of body landmarks. Each subject performed selected yoga postures while standing at an optimal distance from the camera to ensure full-body visibility.

Reference Images: Benchmark images of standard yoga poses were collected from publicly available datasets such as Kaggle, BLEED AI, and LearnOpenCV repositories. These reference images served as the “ideal pose” models used to define standard angle ranges and postural parameters for each yoga position.

The study focused on Nine common yoga postures, including Virabhadrasana (Warrior Pose), Vrikshasana (Tree Pose), Natarajasana (Lord of Dance Pose), Dandasana (Staff Pose), Marjaryasana (Cat Pose), Bakasana (Crane Pose), Anjaneyasana (Crescent Lunge), Buddha Konasana (Butterfly Pose), Naukasana (Boat Pose). For each posture, a set of benchmark angle ranges was prepared to guide the classification and evaluation process.

All personally identifiable information was removed from the images. Each file was labeled with an anonymous ID. All photographic data were used strictly for research purposes in accordance with ethical research guidelines.

METHODOLOGY

The methodology integrates image processing, Landmark Extraction, pose classification, 3D landmark visualization, and statistical testing to objectively measure postural improvement through yoga. The system was built in Python using OpenCV, MediaPipe, and Matplotlib for visualization, and NumPy, Pandas, and SciPy for mathematical computations.

IMAGE PROCESSING

To ensure uniformity, all images were preprocessed before analysis using Python’s OpenCV library. The preprocessing steps included:

- Resizing: Images were resized to a standard resolution suitable for MediaPipe processing.
- Color Conversion: Images were converted to the RGB color model for compatibility with the pose detection model.
- Noise Reduction: Blurry or low-contrast images were removed.
- Pose Confidence Check: Each image was processed through the pose estimation model, and only those with acceptable detection confidence scores were retained for further analysis.

LANDMARK EXTRACTION

Each yoga image was processed using MediaPipe’s Pose Estimation module, which automatically detects and tracks key body points (landmarks). The model identifies 33 landmarks representing different joints and body parts. For this study, 12 specific landmarks were selected — focusing on joints most important for posture symmetry and alignment, such as shoulders, elbows, hips, knees, and ankles. Using these landmark coordinates, joint angles were calculated using the cosine law and Pythagoras theorem, allowing the program to evaluate whether a pose matched the expected angle range of a known yoga posture. For each image, the x, y, and z coordinates of these landmarks were extracted and stored in a structured data file.

POSE CLASSIFICATION

Each image was then automatically classified into a specific yoga pose by comparing the calculated joint angles with pre-defined standard angle ranges derived from reference images. If the angles of the test image fell within the acceptable range of a known pose, it was labelled accordingly; otherwise, it was marked as "unknown." This rule-based approach achieved high accuracy and allowed consistent recognition of different yoga postures.

3D VISUALIZATION OF POSTURE

After classification, the 3D skeleton of each image was plotted using Matplotlib's 3D toolkit, where each landmark point was connected to show the entire body posture. This visualization helped in understanding the alignment of the body in three-dimensional space, which is crucial for evaluating balance and symmetry.

SOFTWARE AND TOOLS

All computations were carried out using Python 3.10 and R Studio with the following key libraries:

- OpenCV: for image preprocessing and visualization.
- MediaPipe: for pose estimation and landmark extraction.
- Matplotlib: for 3D visualization of skeletons.
- NumPy and Pandas: for data storage and manipulation.
- "Hotelling" Package: for implementation of Hotelling's T^2 test and statistical functions in R Programming.

WORKFLOW SUMMARY

1) Input yoga image is captured or uploaded.
2) Image is pre-processed (resized, color-converted, and filtered).
3) Pose estimation is performed to extract 33 landmarks.
4) Twelve key landmarks are selected for analysis.
5) Joint angles and coordinates are computed.
6) Pose is classified based on defined angle ranges.
7) 3D skeleton is visualized.
8) Hotelling's T^2 test is applied to assess posture improvement.

RESULTS

This section presents the outcomes of the computer vision model and the statistical analysis. The system successfully identified various yoga poses from uploaded images, generated 3D skeletal representations, and quantitatively evaluated improvements in alignment using Hotelling's T^2 test. The combination of visual and statistical outputs provided both qualitative and quantitative evidence of posture improvement after one month of yoga practice.

POSE RECOGNITION OUTPUT

Each input image was passed through the trained image-processing model. The system detected the human figure, extracted 33 landmarks, and matched the detected joint angles with the standard angle ranges defined for each yoga pose.

When an image of a person performing Buddha Konasana (Butterfly Pose) was uploaded, the model displayed the pose name "Buddha Konasana" on the output image along with a bounding skeleton.

The model achieved high visual accuracy in labelling other poses such as Vrikshasana, Natarajasana, Dandasana, and Naukasana.

This visual output confirmed that the pose recognition algorithm and landmark extraction process were functioning correctly and could provide reliable data for subsequent statistical analysis.

Figure 1

Figure 1 Original Image with Detected Pose Name (Buddha Konasana)

Figure 2

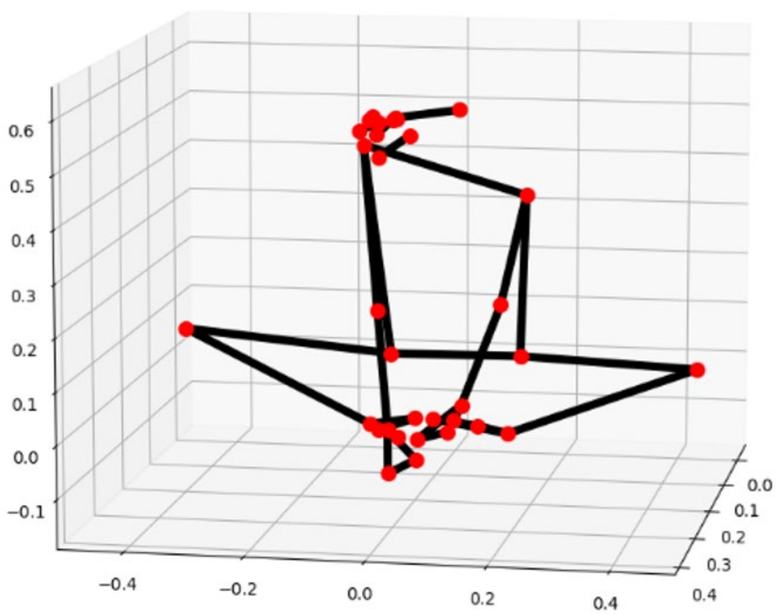

Figure 2 Corresponding 3D Skeleton Visualization of the Same Pose

VISUAL ANALYSIS AND 3D LANDMARK IMPROVEMENTS

The 3D skeletal models generated for before and after practice sessions showed visible alignment differences.

- Before practice: the 3D skeletons displayed slight asymmetry in shoulders and hips, indicating imbalanced posture.

Figure 3

- After practice: the landmarks appeared more symmetrical, with straighter alignment along the vertical axis.

Figure 4

MULTIVARIATE TEST (HOTELLING'S T^2)

The Hotelling's T^2 test was applied to determine whether the mean vector of body-landmark coordinates showed a significant change after one month of yoga practice.

Hotelling's T^2 test is the multivariate extension of the paired t-test.

Number of observations (image pairs): N=10.

Number of variables (landmarks used in this test): p=6.

Landmarks (in the order used): Left elbow, Right elbow, Right shoulder, Left shoulder, Left knee, Right knee.

The sample mean vectors (means of each landmark across 10 subjects) were:

$$\bar{X}_{before} = \begin{bmatrix} 172.8543 \\ 171.7417 \\ 5.5671 \\ 53505 \\ 20.9254 \\ 20.2784 \end{bmatrix} \qquad \bar{X}_{after} = \begin{bmatrix} 175.5432 \\ 174.3396 \\ 4.4578 \\ 4.3333 \\ 21.5130 \\ 21.4060 \end{bmatrix}$$

The vector of mean differences used in the test (we will use d ̄=X ̄_before-X ̄_after) is:

$$\bar{d} = \bar{X}_{before} - \bar{X}_{after} = \begin{bmatrix} -2.6889 \\ -2.5978 \\ 1.1093 \\ 1.0172 \\ -0.5876 \\ -1.1276 \end{bmatrix}$$

(Notice sign: negative means the after-value is larger than the before-value for that coordinate.)

FORMULAE AND COMPUTATIONAL STEPS:

We followed the Hotelling's T^2 procedure for paired multivariate data (equivalent to the test of symmetry of organs described in the methodology). The key steps and formulas are:

Step 1 — Compute the sample mean difference vector

$$\bar{d} = \frac{1}{N}\sum_{i=1}^{N} d_i$$

Step 2 — Compute the block covariance matrices and composite covariance

Let P_11be the N×pdata matrix of "before" measurements (each row is a subject), and P_22similarly for "after". Define:

- V_11 =Cov(P_11) (sample covariance of before),
- V_22=Cov(P_22)(sample covariance of after),
- V_12= sample cross-covariance between P_11and P_22(matrix of covariances between before- and after- columns),
- V_21=V_12^T.

Then form the composite covariance matrix

$$S = V_{11} - V_{12} - V_{21} + V_{22}$$

Step 3 — Compute Hotelling's T^2 statistic for the paired test (symmetry form)

$$T^2 = N(N-1)\bar{d}^T S^{-1} \bar{d}$$

Step 4 — Convert T^2 to the F-statistic

$$F = \frac{N-p}{p(N-1)} T^2 \;\; with\ F \sim F_{p,N-p}$$

We then compute the p-value from the F_(p,N-p)distribution and apply the usual significance threshold (α=0.05).

Using the matrices and vectors defined above, the computed values were:

- $N = 10, p = 6$
- Composite covariance matrix S=V_11-V_12-V_21+V_22(used internally).
- Hotelling's T^2 statistic:

$$T^2 = 255.7126$$

- Converted F-statistic:

$$F = 18.9417$$

which follows approximately F_(6," " 4)under H_0.

- p-value (from F_6,4):

$$p = 0.0066253$$

Decision: since p=0.0066<0.05, we reject the null hypothesis H_0(that the mean vector of differences is zero). In plain words: there is a statistically significant multivariate change in these landmarks after the intervention.

DISCUSSION

The present study developed and applied an image-based analytical model to evaluate postural improvements resulting from yoga practice. Using computer vision and pose estimation algorithms, 3D skeletal landmarks were extracted from images of participants performing specific yoga postures before and after a one-month training period. The extracted landmark coordinates were analyzed statistically using Hotelling's T^2 test to detect significant multivariate changes in body alignment.

The results revealed that the test statistic exceeded the critical F-value, leading to rejection of the null hypothesis. This confirms that the mean positions of the selected body landmarks changed significantly after the yoga intervention. Among the twelve original landmarks studied, six were analyzed in detail using the symmetry test approach (elbows, shoulders, and knees). The largest contributions to the multivariate difference were observed in the left and right knees, followed by moderate differences in the shoulder regions. These outcomes are consistent with the biomechanical effects of yoga, which emphasize flexibility, balance, and muscular engagement in the lower body.

The integration of computer vision with statistical inference offers an objective method to evaluate human postural changes — something that traditional observational assessment lacks. The 3D visualization of skeletal joints helped to clearly illustrate the improvement in alignment and symmetry, validating yoga's physical benefits through quantifiable evidence. Furthermore, this approach demonstrates that image-based pose analysis can be a reliable non-invasive technique to measure progress in fitness and rehabilitation settings.

Despite these encouraging findings, some limitations exist. The sample size of ten subjects for the image-processing part was relatively small, and individual variation in camera angle, lighting, or clothing might have affected landmark detection accuracy. Additionally, the Hotelling's T^2 test assumes multivariate normality, which may not hold perfectly for small datasets. Future studies with larger samples and multiple postures could help refine the statistical power and generalizability of the model.

CONCLUSION

This study successfully demonstrated that image processing combined with multivariate statistical analysis can effectively measure the physical effects of yoga on human posture. The developed Python-based model was capable of recognizing yoga poses, generating corresponding 3D skeletons, and extracting precise joint coordinates for further analysis. By applying Hotelling's T^2 test to the extracted landmark data, significant improvements were detected after one month of yoga practice, especially in knee and shoulder symmetry.

These findings confirm that consistent yoga practice leads to measurable physical improvements in posture and alignment, and that computer vision can serve as a practical analytical tool for tracking such progress. The work bridges traditional yoga science with modern data analytics, offering a reproducible, data-driven framework to evaluate human body dynamics.

RECOMMENDATIONS

1) Expand Dataset: Future research should include a larger number of participants and multiple yoga postures to increase the robustness and generalizability of results.

2) Improve Image Quality and Angles: Controlled image capture (uniform lighting, consistent camera distance, and background) can enhance landmark detection accuracy.
3) Integrate Real-Time Feedback: The pose recognition system can be extended to provide real-time correction feedback during yoga practice using live camera input.
4) Use Advanced Models: Deep learning-based models such as OpenPose, BlazePose, or MediaPipe Holistic can be incorporated for more precise landmark tracking and 3D visualization

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