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Computer Vision based Fitness Assessment using Mobile Devices

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***Abstract*— The identification and development of athletic talent in various regions remain a significant challenge due to limited access to professional coaching and standardized evaluation system. To address this problem, the paper presents an AI powered Fitness Assessment platform designed to democratize sports talent identification. The suggested system uses real-time computer vision techniques to assess physical fitness metrics using standardized scoring, including pushups, squats, vertical jumps, planks, endurance runs, and shuttle runs. Benchmarking based on gender and age guarantees equity. It integrates pose estimation through media pipe based skeletal tracking, motion analysis, repetition count-ing via custom state machine logic, biomechanical validation algorithms for form assessment. A more scalable, transparent, and inclusive framework for national athletic talent discovery is provided by automating manual and resource-intensive fitness testing procedures. This is especially important in developing nations where traditional systems struggle with affordability, accessibility, and scalability.**

***Keywords*— Computer vision, Pose estimation, Fitness assessment, Talent identification, Performance Benchmarking, Biomechanical analysis.**

I. INTRODUCTION

Many young athletes in rural India work hard to improve their skills but often remain undiscovered due to their location.[1] Talent identification through formal processes, video analysis, trials and coaching are rarely accessible to children in rural areas of India. The conventional model of talent identification, which typically involves migrating to the urban trial, is time consuming, expensive and hence not accessible to most of the players. Their potential is often overlooked, not due to a lack of ability, but because the pathway to recognition is inaccessible. This imbalance raises an important question - Can technology make talent discovery more equitable and scalable? Recent advancements in Artificial Intelligence and computer vision enable accurate human pose estimation using smartphone cameras[2]. In fitness, automated repetition counting, posture validation, and performance tracking are now possible, with some low-cost solutions suitable for resource-limited settings [3, 4]. However, current fitness testing methods fall short in providing automated assessments of athlete performance. This work introduces a groundbreaking AI-based mobile application that standardizes fitness testing through pose estimation [3, 5, 6], biomechanical analysis, normalized scoring techniques, and a centralized performance discovery portal, offering a scalable solution for assessing athletic ability. [2]

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II. Related Work

A. Traditional Fitness Evaluation and Experimental Sports Studies

Traditional fitness assessment methods, such as vertical jump tests and shuttle runs [7], are commonly used in sports science to evaluate performance metrics like anaerobic power, jump height, coordination, and endurance. These tests, usually conducted in controlled environments like schools, offer reliable benchmarks for athlete performance and allow for comparisons across training programs. However, they have limitations, such as a dependence on manual supervision, the necessity for controlled settings, and difficulties in scaling to larger groups. Moreover, they lack automation and real-time feedback, highlighting the need for more advanced digital assessment systems.

B. Normative Physical Fitness Standards for Indian Adolescents

Research on physical fitness standards for Indian adolescents has established age- and gender-specific benchmarks using standardized tests and percentile curves [8]. These studies highlight performance variations among demographic groups and offer reference points for assessing individual fitness levels. However, current methods rely on manual evaluation [9], lacking integration with artificial intelligence for real-time analysis. This gap underscores the need for scalable digital solutions to enhance modern fitness assessment systems.

C. Real-Time Pose Estimation for Mobile Devices

Recent advancements in deep learning have enabled real-time human pose estimation on mobile devices [3]. These systems extract key skeletal points from images or videos, enabling precise tracking of human movements and supporting automated exercise analysis and repetition counting. However, current pose estimation systems emphasize detection accuracy over domain-specific applications like fitness validation or scoring, highlighting a gap between technology and practical fitness evaluation.

III. Equations

A. Test Specific Methods

Pushups Test

Algorithm Name: Pushups rep counter using joint angle state machine.
Key Formula (Elbow Angle Calculation):

$$\theta = \left(\tan^{-1}\frac{c_y - b_y}{c_x - b_x} - \tan^{-1}\frac{a_y - b_y}{a_x - b_x} \right) \times \frac{180}{\pi} \qquad (1)$$

Squats Test

Algorithm Name: Knee-Angle Depth-Based Squat Counter
Key Formula (Knee Angle):

$$\theta_{\text{knee}} = \angle(\text{hip}, \text{knee}, \text{ankle}) \qquad (2)$$

Plank Test

Algorithm Name: Spine Alignment Stability Analyzer
Key Formula (Alignment Angle):

$$\theta_{\text{alignment}} = \angle(\text{shoulder}, \text{hip}, \text{ankle}) \qquad (3)$$

Vertical Jump Test

Algorithm Name: Hip Displacement Jump Height Estimator
Key Formula:

$$\text{Relative Jump} = y_{\text{standing}} - y_{\text{peak}} \qquad (4)$$

Shuttle Run Test (4x10m)

Algorithm Name: Center-of-Mass Direction Change Detector Key Formula (Center of Mass):

$$\text{COM}_x = \frac{x_{11} + x_{12} + x_{23} + x_{24}}{4} \qquad (5)$$

Endurance Run

Algorithm Name: Accelerometer Peak Based Step Counter

Key Formula (Acceleration Magnitude):

$$\text{Magnitude} = \sqrt{x^2 + y^2 + z^2} \quad (6)$$

IV. TABLES

TABLE I. TECH STACK

Layer	Technology	Purpose
Frontend	React Native (Expo)	Cross-platform mobile application
AI Services	Python FastAPI	Pose estimation, analysis, scoring
API Backend	Node.js Express	Authentication, benchmarking
Pose Estimation	MediaPipe Pose Landmarker v0.10	33-landmark body pose detection
Face Verification	DeepFace.verify()	Identity verification
Signal Processing	NumPy, SciPy	Angle computation, step counting
Database	MongoDB	Storage of users and results

TABLE II. FITNESS TESTS

Sr No.	Test	Fitness Component	Measurement	Duration
1	Push-ups	Upper body endurance	Rep count + form accuracy	1 min
2	Squats	Lower body endurance	Rep count + depth quality	1 min
3	Plank	Core stability	Hold duration	Until failure
4	Vertical Jump	Explosive power	Jump height (cm)	3 attempts
5	Shuttle Run	Agility and speed	Completion time	Timed
6	Endurance Run	Cardiovascular endurance	Distance (meters)	12 min

V. FIGURES

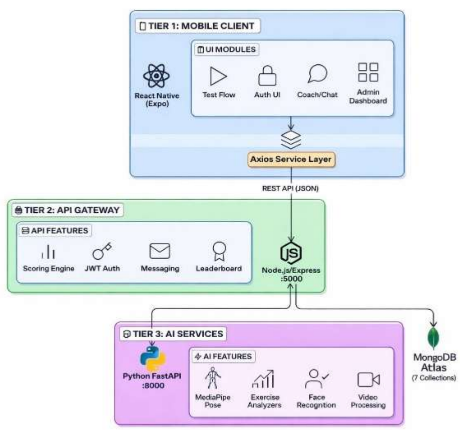


Fig. 1 Architecture Diagram

The system has a three-tier architecture consisting of a mobile client, API gateway, and AI microservice. The React Native app offers athletes and coaches tools for test execution, progress tracking, and communication. The Node.js API gateway handles authentication and data security with MongoDB, while the FastAPI microservice per-forms pose estimation, exercise analysis, and face verification, ensuring scalability and efficient processing.

VI. ALGORITHMS

A. Joint Angle Computation

Algorithm: ComputeAngle(a, b, c)

Require: Points $a = (a_x, a_y)$, $b = (b_x, b_y)$, $c = (c_x, c_y)$

Ensure: Angle $\theta \in [0°, 180°]$

1: $r \leftarrow |\arctan 2(c_y - b_y, c_x - b_x) - \arctan 2(a_y - b_y, a_x - b_x)|$

2: $\theta \leftarrow r \times \frac{180}{\pi}$
3: if θ > 180 then
4: θ ← 360 − θ
5: end if
6: return θ

B. Visibility-Weighted Side Selection

Algorithm: SelectBestSide Require: Landmark visibility values Ensure: Best angle selection
1: $V_L \leftarrow \min(\mathrm{vis}(L_1), \mathrm{vis}(L_2), \mathrm{vis}(L_3))$
2: $V_R \leftarrow \min(\mathrm{vis}(R_1), \mathrm{vis}(R_2), \mathrm{vis}(R_3))$
3: $\tau \leftarrow 0.15$
4: if $V_L - V_R > \tau$ then
5: return left angle
6: else if $V_R - V_L > \tau$ then
7: return right angle
8: else
9: return $(angle_L + angle_R)/2$
10: end if

C. Rep Counting FSM

Algorithm: CountReps Require: Frame sequence Ensure: Number of repetitions
1: state ← NULL
2: count ← 0
3: for each frame do
4: compute angle
5: if angle > UP threshold then
6: if state = DOWN then
7: count ← count + 1
8: end if
9: state ← UP
10: else if angle < DOWN threshold then
11: state ← DOWN
12: end if
13: end for
14: return count

D. Plank Analysis

Algorithm: AnalyzePlank Require: Keypoints, FPS Ensure: Duration and breaks
1: validFrames ← 0
2: breaks ← 0
3: badCount ← 0
4: for each frame do
5: compute body alignment
6: if form is good then
7: validFrames ← validFrames + 1
8: badCount ← 0
9: else
10: badCount ← badCount + 1
11: end if
12: if badCount > threshold then
13: breaks ← breaks + 1
14: badCount ← 0
15: end if
16: end for
17: duration ← validFrames/FPS
18: return duration, breaks

E. Vertical Jump Analysis

Algorithm: AnalyzeVerticalJump Require: Keypoints
Ensure: Jump height
1: estimate body scale
2: detect peak frame
3: compute displacement
4: height ← displacement × scale
5: return height

VII. METHODOLOGY

A. Pose Estimation Pipeline

The video-to-analysis pipeline operates in five stages:

- Video Ingestion: The MP4 video is read using OpenCV's VideoCapture. Frame rate and duration are extracted from metadata.[10]
- Frame Sampling: Every third frame is processed to balance accuracy and computational cost (approximately 10 FPS for a 30 FPS video).
- Pose Detection: Each frame is converted from BGR to RGB and analyzed with MediaPipe Pose Landmarker, resulting in 33 landmarks with normalized coordinates and visibility scores. .[11]
- Landmark Serialization: The 33 × 4 landmark array is stored per frame. Frames without detection are recorded as null.
- Analyzer Invocation: The processed landmark sequence, FPS, and duration are passed to exercise-specific analyzers.

B. Angle Computation

Joint angles are computed using:

$$\theta = |\arctan 2(c_y - b_y, c_x - b_x) - \arctan 2(a_y - b_y, a_x - b_x)| \times 180$$

as shown in section 6.1 where a, b, and c are landmark coordinates and b is the vertex. If θ > 180○, it is adjusted as 360○ − θ.

C. Exercise-Specific Analyzers

Push-Up Analyzer
A finite state machine is used:

- UP state: elbow angle > 160○
- DOWN state: elbow angle < 145○

A repetition is counted when transitioning from DOWN to UP. Quality evaluation includes:

- Extension quality (Excellent, Good, Partial)
- Body alignment based on shoulder-hip-ankle angle
- Perfect form if extension > 170○ and alignment > 85%

Squat Analyzer
Knee angle is used:

- UP: > 160○
- DOWN: < 120○

Depth classification:

- Full: < 90○
- Parallel: < 110○
- Partial: < 120○
- Shallow: ≥ 120○

Plank Analyzer
Plank is evaluated using duration and alignment:

- Ideal alignment: ≈ 180○
- Good form: 155○ ≤ θ ≤ 190○
- Perfect form: stricter angle and elbow constraints

The hold is divided into 10-second segments for detailed evaluation. Breaks are detected if bad form persists for 0.5 seconds.

Vertical Jump Analyzer
Four phases are detected: Stance, Loading, Flight, and Landing. Height is estimated using:
scale = (avg_height * 0.95) / median(nose_to_ankle) jump_height = displacement * scale

D. Anti-Cheat Detection System

The system includes hard and soft checks.

Hard checks (disqualification):
- Insufficient data (less than 3 seconds)
- Person detection below 60%
- Frozen video (very low variance)
- Invalid landmark extraction

Soft flags (warnings):
- Large movement
- Sudden position changes
- Repeated motion loops
- Incorrect camera angle
- Possible speed manipulation

The ablation analysis showed that removing the anti-cheat made the system vulnerable to invalid inputs, while disabling penalty-based scoring reduced fairness, highlighting the importance of both for a reliable and balanced system.

E. Face Verification

Face verification is performed using a deep learning-based encoding:
- Extract 128-dimensional embeddings
- Compute Euclidean distance
- Confidence = 1 − d
- Match threshold = 0.6

VIII. RESULTS

A. System Performance

The platform streamlines the fitness assessment process, handling athlete registration, test execution, AI analysis, scoring, and progress tracking on Android smartphones. Push-Ups and Squats: For 60-second videos, around 200 frames were processed. Analysis took 8 to 12 seconds, yielding outputs like repetition count, accuracy, and form evaluation.
Plank: For durations of 60 to 180 seconds, the system processed about 200 to 600 frames, with analysis times of 10 to 30 seconds, resulting in performance insights and posture evaluations.
Vertical Jump: Short clips of 5 to 10 seconds required processing 30 to 50 frames, with analysis completed in 2 to 4 seconds. The system estimated jump height, flight time, and phase quality.
Shuttle Run: Videos of 10 to 15 seconds required around 50 frames and were pro-cessed in 1 to 2 seconds, producing time, turn count, and performance score.[12] Endurance Run: This test relied on sensor data instead of video frames completed in less than 1 second, generating step count, distance, and pace.

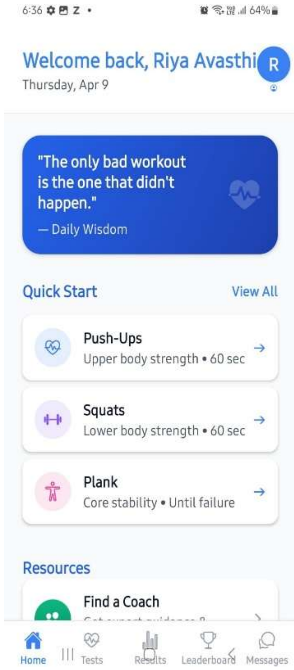
B. Scoring Accuracy

The scoring mechanism adapts to different user profiles using benchmark-based nor-malization. The system ensures fairness by considering age and gender variations. Additionally, penalties are applied for poor form, preventing inflated scores due to incorrect repetitions. The inclusion of percentile ranking further helps in comparing performance relative to other users.

C. Limitations

Despite strong performance, the system has certain limitations:
- Pose estimation accuracy decreases under poor lighting or loose clothing conditions. [5]
- Extreme camera angles can still affect landmark detection.

- Jump height estimation may have a small error margin due to generalized body proportions.
- Endurance tracking depends on sensor accuracy, which varies by device.
- Face verification may fail under significant appearance changes.



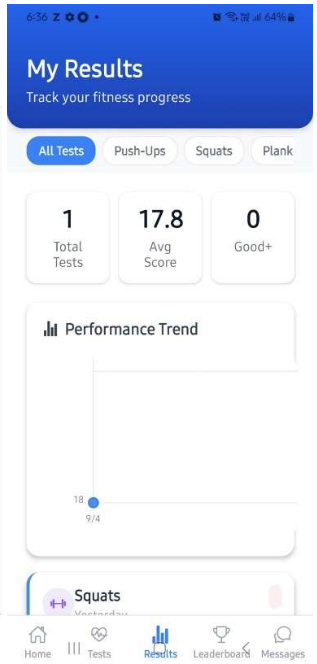


Fig. 2 Result output

Fig. 3 Generated score and performance evalua-tion

IX. DISCUSSION

The proposed system demonstrates that computer vision can enable automated fitness assessments using pose estimation and tailored analysers. It evaluates exercises and provides feedback by extracting body landmarks from regular videos without requir-ing special equipment. The system counts repetitions and assesses movement quality for exercises like push-ups and squats, helping users improve form. It can also estimate jump height for vertical jumps, though accuracy may vary due to body propor-tion assumptions[4, 7, 13]. An anti-cheat mechanism improves reliability by detecting invalid inputs, but some unusual cases may still go unnoticed [8, 14]. Limitations include dependence on video quality, lighting, and camera angle.

X. CONCLUSION

This paper presented UDAAN, an AI-powered mobile platform for automated phys-ical fitness assessment. The System integrates MediaPipe pose estimation, custom exercise analyzers, an anti-cheat detection system, and face recognition for identity verification, offering standardized fitness testing on smartphones. The system utilizes computer vision to count exercise repetitions, measure plank durations, estimate jump heights, and assess form quality through joint angle analysis, while ensuring anti-cheat detection.[9, 15, 16] UDAAN's architecture is a React Native mobile client, Node.js API gateway, and Python FastAPI AI microservice — provides a scalable, extensible foundation for nationwide deployment.[17]

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