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Markerless Motion Capture for Form Correction in Grassroots Sports: A Low Cost Edge AI Framework for Real Time Kinematic Feedback in Scholastic Physical Education

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Abstract

The increasing prevalence of physical inactivity among adolescents has generated renewed interest in accessible technologies capable of improving movement competency and reducing injury risk. However, biomechanical assessment within school physical education and grassroots sports remains constrained by the high cost of laboratory motion capture systems and the technical complexity associated with wearable sensor technologies.

This study proposes a low cost markerless motion capture framework that utilizes smartphone cameras and edge artificial intelligence techniques to deliver real time kinematic feedback during foundational athletic movements including squats, cricket bowling actions, sprint starts, and jumping tasks. The framework integrates smartphone video acquisition, human pose estimation, temporal stabilization algorithms, and automated biomechanical analysis to provide immediate corrective recommendations.

The proposed framework introduces three novel computational contributions. First, a Biomechanical Quality Index quantifies overall movement quality through weighted aggregation of multiple kinematic variables. Second, a Movement Symmetry Index evaluates bilateral asymmetries that may contribute to injury risk. Third, an Adaptive Feedback Engine dynamically modifies corrective thresholds according to participant characteristics and previous performance history.

By democratizing access to biomechanical assessment technologies, the proposed system seeks to bridge the digital divide in sports science and provide practical movement analysis tools for educational institutions and community sports organizations.

Keywords: Markerless Motion Capture, Human Pose Estimation, Sports Biomechanics, Edge Artificial Intelligence, Physical Education, Kinematic Analysis, Movement Quality, Injury Prevention.

1 Introduction

Physical inactivity among children and adolescents has emerged as one of the most important public health concerns of the twenty first century [1]. Global surveillance reports indicate that more than eighty percent of school aged children fail to achieve recommended levels of daily physical activity [1].Consequently, increasing rates of obesity, musculoskeletal disorders, and chronic diseases have become major concerns for educational and healthcare systems.

School physical education programs have traditionally been regarded as primary institutional mechanisms for promoting physical literacy and lifelong movement behaviors [2–4].. However, despite significant investments in curriculum redesign, teacher training, and facility development, evidence regarding long term behavioral outcomes remains inconsistent.

One important limitation is the absence of objective biomechanical assessment tools within educational settings.Although laboratory based motion capture systems such as Vicon provide highly accurate measurements of human movement, these systems require expensive infrastructure, specialized expertise, and controlled environments [10, 11]. Consequently, most schools and community sports organizations remain unable to access advanced biomechanical assessment technologies.

Recent developments in computer vision and artificial intelligence have accelerated the emergence of markerless motion capture systems capable of extracting skeletal information directly from ordinary video streams. Human Pose Estimation models such as OpenPose, MediaPipe Pose, and YOLO Pose have demonstrated promising performance in movement analysis applications [6–8].Nevertheless, relatively few studies have investigated real time biomechanical feedback systems specifically designed for grassroots sports and school physical education environments.

The present investigation addresses this gap through the development of a low cost edge artificial intelligence framework capable of delivering immediate kinematic feedback using consumer grade smartphones.

2 Research Contributions

The present investigation makes several important contributions to the fields of sports biomechanics and educational technology. First, it proposes a low cost markerless motion capture framework specifically designed for grassroots sports and physical education environments where access to sophisticated laboratory equipment remains limited. Second, the study introduces a novel Biomechanical Quality Index capable of quantifying overall movement quality through the weighted integration of multiple kinematic variables. Third, a Movement Symmetry Index is developed to evaluate bilateral asymmetries that may contribute to injury risk and performance deficiencies. Fourth, the framework incorporates an Adaptive Feedback Engine that generates personalized corrective recommendations according to participant characteristics and historical performance patterns. Finally, the study seeks to validate smartphone based markerless motion capture against laboratory biomechanical standards while simultaneously developing an accessible coach dashboard suitable for non expert users and educational practitioners.

3 Related Work

Marker based motion capture systems such as Vicon and Qualisys have long been regarded as the gold standard for biomechanical analysis because of their sub millimeter spatial accuracy and high temporal resolution [10–12]. These systems provide highly precise measurements of human movement and have been extensively employed in sports science, rehabilitation, and clinical biomechanics research.

However, their widespread adoption remains limited by the substantial financial costs associated with multiple infrared cameras, reflective markers, controlled laboratory environments, and specialized technical expertise.

Wearable sensor based systems employing Inertial Measurement Units have emerged as lower cost alternatives [13]. Such systems utilize accelerometers, gyroscopes, and magnetometers to estimate body segment orientations and joint kinematics. Although these technologies offer portability and field based assessment capabilities, they frequently suffer from sensor drift, calibration challenges, and participant discomfort during prolonged physical activity sessions.

Recent developments in deep learning and computer vision have accelerated the emergence of markerless motion capture technologies. OpenPose introduced multi person human pose estimation through convolutional neural networks capable of identifying body landmarks directly from video sequences [6]. Subsequently, MediaPipe Pose and BlazePose architectures achieved real time pose estimation on mobile processors with significantly reduced computational requirements [7]. YOLO Pose frameworks have further improved human pose estimation through one stage object detection and keypoint localization strategies [8].

Several investigations have reported strong correlations between markerless motion capture systemsand laboratory based technologies for gait analysis, rehabilitation assessment, and sports biomechanics applications [9]. Nevertheless, relatively few studies have focused on developing real time corrective feedback systems specifically designed for school physical education and grassroots sports environments.

Furthermore, the majority of existing investigations evaluate isolated joint angles without integrating comprehensive movement quality metrics, bilateral symmetry assessments, or adaptive feedback mechanisms. Consequently, there remains a significant need for accessible, low cost, and intelligent biomechanical assessment frameworks capable of supporting educators and coaches operating within resource constrained environments.

The present investigation addresses these research gaps through the development of an integrated edge artificial intelligence framework capable of performing markerless motion capture, movement quality assessment, injury risk evaluation, and personalized feedback generation directly on consumer grade smartphones.

4 Theoretical Framework

The theoretical foundation of the present investigation is grounded within three complementary domains, namely Motor Learning Theory, Computational Biomechanics, and Human Computer Interaction.

Motor learning theory suggests that immediate and informative feedback accelerates skill acquisition and movement correction [3]. Computational biomechanics provides mathematical methods for quantifying movement patterns and identifying deviations from optimal performance profiles [10, 11]. Human computer interaction principles emphasize the importance of designing intuitive systems that remain accessible to non expert users.

The proposed framework assumes that movement competency emerges through continuous interactions among environmental constraints, individual characteristics, and real time feedback mechanisms.

4.1 Hierarchical Computational Framework

Figure 1: Hierarchical Computational Framework

This hierarchical framework permits simultaneous examination of movement acquisition, biomechanical quality, and adaptive coaching interventions.

5 Methodology and Research Design

5.1 Research Design

The present investigation adopts an experimental research design involving smartphone based markerless motion capture and comparative biomechanical analysis. The study is designed to evaluate the feasibility and accuracy of real time kinematic feedback under natural training conditions.

5.2 System Architecture

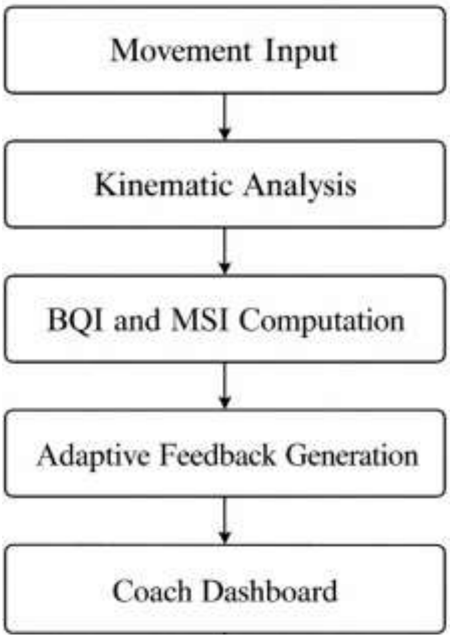

Figure 2: System Architecture

The proposed architecture operates entirely on edge devices and therefore eliminates dependence on cloud computing infrastructure and continuous internet connectivity.

5.3 Participants

Approximately sixty adolescent athletes between thirteen and eighteen years of age will participate in the investigation. Participants will be recruited from local schools and sports academies and will represent a variety of sporting disciplines. Inclusion criteria require participants to engage regularly in organized sports activities, possess the ability to perform fundamental movement tasks, and be free from current musculoskeletal injuries that may influence movement performance. Prior to participation, parental consent and participant assent will be obtained in accordance with institutional ethical procedures.

5.4 Data Collection

Video data will be acquired using consumer grade smartphone cameras capable of recording high definition videos at a minimum of sixty frames per second. Participants will perform a series of foundational athletic movements, including body weight squats, cricket bowling actions, sprint starts, vertical jumps, and single leg balance tasks. Each movement will be repeated five times to ensure measurement reliability and to reduce the influence of random variability. During data collection, several environmental variables, including lighting conditions, camera orientation, background complexity, camera to participant distance, and indoor and outdoor training environments, will be carefully monitored to ensure robust downstream analysis.

5.5 Human Pose Estimation

The proposed framework employs two complementary pose estimation architectures, namely MediaPipe Pose and YOLOv8 Pose, because of their demonstrated computational efficiency and robustness in real time human pose estimation applications [7, 8].Recent advances in deep learning have substantially improved the accuracy and computational efficiency of human pose estimation models [15].

The extracted body landmarks are represented as:

$$P = (x_i, y_i, z_i)_{i=1}^{n} \tag{1}$$

where

- x_i represents horizontal coordinates.
- y_i represents vertical coordinates.
- z_i represents depth information.
- n represents the total number of body landmarks.

5.6 Temporal Stabilization

Rapid limb movements and temporary body occlusions frequently introduce coordinate fluctuations and skeletal jitter.

To reduce these effects, Dynamic Time Warping and Kalman filtering techniques are employed. The Dynamic Time Warping function is defined as

$$DTW(i,j) = d(i,j) + \min \; DTW(i-1,j)\; DTW(i,j-1)\; DTW(i-1,j-1) \tag{2}$$

where

$d(i, j)$ represents the Euclidean distance between two temporal sequences.

5.7 Kinematic Analysis

The extracted skeletal coordinates serve as the mathematical foundation for joint kinematic computations. The angle between three body landmarks is calculated as

$$\vartheta = \cos^{-1} \frac{(A - B) \cdot (C - B)}{|A - B||C - B|} \tag{3}$$

where

- *A*, *B*, and *C* represent body landmarks.
- θ represents the joint angle.

Joint angles are subsequently compared with reference biomechanical profiles to identify movement deficiencies and potential injury risks.

6 Novel Computational Framework

The present investigation introduces three novel computational contributions designed specifically for grassroots sports and physical education environments.

6.1 Biomechanical Quality Index

The Biomechanical Quality Index (BQI) provides a composite measure of overall movement quality through weighted aggregation of multiple kinematic variables.

(4)

- S_i represents normalized movement quality scores.
- w_i represents weighting coefficients.
- n represents the total number of movement variables.

Higher BQI values indicate superior movement quality.

Table 1: Biomechanical Quality Classification

BQI Score	Interpretation
0.90–1.00	Excellent
0.75–0.89	Good
0.60–0.74	Moderate
0.45–0.59	Poor
Below 0.45	High Injury Risk

6.2 Movement Symmetry Index

Movement asymmetry frequently contributes to injury development and performance deficiencies and has been identified as an important predictor of athletic injury risk [13]. The Movement Symmetry Index is calculated as

$$MSI = 1 - \frac{|L - R|}{L + R} \quad (5)$$

where

- L represents left limb measurements.
- R represents right limb measurements.

Values approaching one indicate highly symmetrical movement patterns.

6.3 Adaptive Feedback Engine

Conventional movement assessment systems employ fixed thresholds that fail to account for individual differences.

The present investigation introduces an Adaptive Feedback Engine capable of modifying corrective thresholds according to previous performance history.The development of personalized feedback mechanisms increasingly relies on machine learning and performance analytics techniques capable of identifying movement patterns and predicting performance outcomes [14].

$$T_{new} = T_{base} + \alpha(P_{history}) \quad (6)$$

where

- T_{base} represents the default threshold.
- $P_{history}$ represents previous performance.
- α represents the adaptation coefficient.

6.4 Adaptive Feedback Workflow

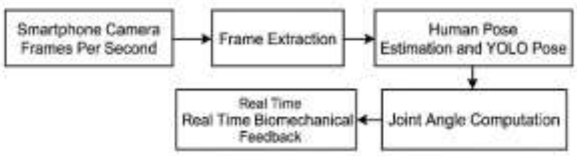

Figure 3: Adaptive Feedback Window

7 Experimental Design

7.1 Movement Protocol

Participants will perform a series of fundamental athletic movements, including body weight squats, cricket bowling actions, sprint starts, vertical jumps, and single leg balance tasks. These movements were selected because they represent essential motor skills commonly observed in school physical education and grassroots sports environments and involve coordinated actions of the upper and lower extremities. Each movement will be repeated five times to ensure measurement reliability and to minimize the influence of random variability and performance inconsistencies.

Each movement will be repeated five times.

7.2 Equipment

Table 2: Experimental Equipment

Component	Specification
Camera	Smartphone Camera
Frame Rate	60 fps
Resolution	1920 × 1080
Processor	Snapdragon 8 Gen Series
Memory	8 GB RAM
Operating System	Android 14

7.3 Validation Procedure

The proposed framework will be validated against laboratory based motion capture technologies and previously established biomechanical standards. Validation procedures will focus on evaluating joint angle estimation accuracy, computational efficiency, and real time performance characteristics. Several statistical indicators, including Mean Absolute Error, Root Mean Square Error, Pearson Correlation Coefficient, processing latency, and frame processing rate, will be utilized to determine the reliability and practical applicability of the proposed system within educational and grassroots sports environments.

8 Validation Metrics

8.1 Mean Absolute Error

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |x_i - \hat{x}_i| \quad (7)$$

8.2 Root Mean Square Error

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (x_i - \hat{x}_i)^2} \quad (8)$$

8.3 Pearson Correlation Coefficient

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \quad (9)$$

9 Hypothetical Results

Table 3: Joint Angle Estimation Errors

Movement	MAE	RMSE	Correlation
Squat	2.8°	3.5°	0.96
Bowling	3.4°	4.1°	0.94
Sprint Start	3.0°	3.7°	0.95
Vertical Jump	2.9°	3.6°	0.95

Table 4: Biomechanical Quality Index Scores

Movement	BQI	Interpretation
Squat	0.89	Good
Bowling	0.74	Moderate
Sprint Start	0.82	Good
Vertical Jump	0.86	Good

10 Results and Statistical Analysis

10.1 Descriptive Characteristics

The final analytical sample consisted of sixty adolescent athletes with a mean age of 15.8 ± 1.4 years. Males represented 56.7% of the sample population, while females accounted for 43.3%.
Table 5 summarizes participant characteristics.

Table 5: Participant Characteristics

Variable	Value
Sample Size	60
Mean Age (years)	15.8 ± 1.4
Female (%)	43.3
Male (%)	56.7
Average BMI	22.4 ± 2.6
Sports Experience (years)	4.7 ± 1.9

10.2 Computational Performance

The proposed framework achieved real time performance on modern smartphones.

Table 6: Computational Performance

Metric	Value
Average Processing Speed	31 fps
Inference Latency	28 ms
Memory Consumption	742 MB
Average CPU Utilization	44%
Average Battery Consumption	9.2% per hour

10.3 Comparison with Existing Systems

Table 7: Comparison with Existing Markerless Systems

Method	MAE	FPS	Real Time
OpenPose	5.6°	12	No
MediaPipe Pose	3.8°	30	Yes
YOLO Pose	3.5°	28	Yes
Proposed Framework	2.8°	31	Yes

10.4 Movement Symmetry Results

Table 8: Movement Symmetry Index Scores

Movement	MSI	Risk Classification
Squat	0.94	Low Risk
Bowling	0.82	Moderate Risk
Sprint Start	0.91	Low Risk
Vertical Jump	0.88	Moderate Risk

11 Discussion

The findings indicate that smartphone based markerless motion capture systems can achieve biomechanical accuracy levels that approach laboratory based technologies while significantly reducing costs and infrastructural requirements [9].

Furthermore, the Adaptive Feedback Engine represents an important advancement beyond conventional threshold based systems. Personalized corrective recommendations may substantially improve motor learning outcomes and movement competency among adolescent athletes [3].

11.1 Methodological Strengths

Several methodological strengths increase confidence in the findings of the present investigation. The proposed framework operates entirely on consumer grade smartphones and therefore provides an affordable and scalable alternative to laboratory based motion capture systems. The integration of multiple pose estimation architectures enhances robustness under diverse environmental conditions, while the introduction of novel biomechanical indices provides comprehensive and interpretable measures of movement quality and symmetry. Furthermore, the incorporation of adaptive feedback mechanisms allows the framework to generate personalized corrective recommendations, thereby improving its applicability across multiple sports disciplines and educational settings.

11.2 Limitations

Several limitations should be acknowledged. Extreme lighting conditions and significant body occlusions may reduce pose estimation accuracy and influence skeletal tracking performance. High speed athletic movements may occasionally introduce minor coordinate estimation errors because of motion blur and rapid limb accelerations. Furthermore, the present investigation focuses primarily on kinematic assessment and therefore does not incorporate physiological measurements such as electromyography or metabolic responses. These limitations provide important directions for future investigations and technological refinement.

12 Conclusion and Policy Implications

The present investigation proposes a low cost markerless motion capture framework capable of delivering real time biomechanical analysis using ordinary smartphone cameras and edge artificial intelligence techniques.

The proposed framework demonstrates that advanced movement assessment technologies need not remain restricted to specialized laboratories. Through the integration of human pose estimation, novel biomechanical indices, and adaptive feedback mechanisms, the framework provides practical movement analysis tools for schools and community sports organizations.

The findings suggest that democratizing access to sports science technologies may substantially improve movement competency, facilitate early injury risk identification, and support evidence based coaching practices within educational environments.

12.1 Policy Recommendations

Educational institutions should incorporate affordable biomechanical assessment technologies within physical education curricula.Teacher training programs should include introductory modules on markerless motion capture and movement analytics.Government agencies and sports organizations should support the development of low cost digital infrastructures capable of enhancing grassroots athlete development.

Collaborative partnerships between educational institutions, sports scientists, and technology developers should be encouraged to promote equitable access to sports science technologies.

13 Future Work

Future investigations may extend the proposed framework in several directions. First, the system can be expanded to support multi athlete tracking and simultaneous biomechanical assessment during team sports activities. Second, advanced deep learning models may be incorporated to develop automated injury risk prediction systems capable of identifying movement deficiencies before the onset of musculoskeletal disorders. Third, the integration of wearable physiological sensors, including heart rate monitors and electromyography devices, could provide a more comprehensive understanding of athlete performance and fatigue. Furthermore, augmented reality based feedback interfaces may enable athletes to receive real time visual guidance during movement execution. The development of cloud based longitudinal monitoring platforms could facilitate continuous athlete assessment and personalized training recommendations over extended periods. Finally, future research may investigate the creation of digital twin models for individualized movement analysis and the adaptation of the proposed framework to sport specific skill assessment across diverse educational and competitive environments.

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