International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 2s, 2025

Real Time Powerlifting Form Assessment using Yolov5 and Mediapipe

Vishwanath Nikhil[1], Dr. Mohammed Abdul Bari[2]
[1]B.E Students, Department Of Artificial Intelligence & Data Science Engineering, ISL Engineering College, Hyderabad.
[2]Professor in CSE , Dean Academics Department Of Artificial Intelligence & Data Science Engineering, ISL Engineering College, Hyderabad.

vishwanathnikhil44@gmail.com

Abstract *This study introduces an on-device, real-time AI posture correction system tailored for the three core powerlifting exercises: bench press, back squat, and conventional deadlift. We employ* ***YOLOv5*** *for efficient person detection, combined with an HSV-based background subtraction mask to dynamically crop the region of interest (ROI), ensuring streamlined processing. To enable accurate, user-tailored feedback, we present the PolyView Kinematic Corpus (PKC), a novel multi-camera 3D landmark dataset recorded from front, side, and oblique angles, capturing concentric and eccentric phases from 150 lifters with diverse body types. Utilizing PKC data, we train only machine learning classification algorithms (e.g., decision trees, LightGBM) to detect subtle joint alignment deviations at rep "bottom" and "lockout" phases, with evaluations showing these methods achieve high accuracy in lift phase classification. Our phase-sensitive feedback system, based on user-calibrated angle bands and temporal smoothing, delivers precise visual overlays and concise audio prompts to guide lifters toward safer, more effective techniques. Deployed via a low-latency web interface, the system provides exercise-specific cues in under 50 ms per frame, helping lifters minimize injury risk and optimize performance without external sensors or complex setup.*

I. INTRODUCTION

The COVID-19 pandemic's restrictive measures compelled many individuals to remain indoors for extended periods, underscoring the vital role of exercise in maintaining both physical health and mental well-being [1], [2]. With gyms closing and outdoor activities curtailed, people turned increasingly to home-based workout routines, sparking a proliferation of online fitness platforms. Applications such as Peloton, Perfect Posture & Healthy Back, and Leg Workouts, Exercises for Men quickly amassed millions of users by offering on-demand classes, customizable workout plans, and basic posture demonstrations [3], [4]. While these tools provided much-needed structure and motivation during lockdowns, their reliance on prerecorded videos and lack of real-time corrective feedback meant that users often practiced without knowing whether their form was safe or effective. For many, this gap translated into frustration, stalled progress, or even risk of injury especially when attempting more complex movements without professional supervision. Among the myriad of exercises promoted by these platforms, compound movements like the bench press, squat, and deadlift stand out for their efficiency in building strength and muscle mass. Unlike single-joint exercises, which isolate specific muscle groups, these multi-joint lifts engage several large muscle groups simultaneously, enabling lifters to handle heavier weights and achieve substantial strength gains. Poor squat form such as allowing the knees to collapse inward or rounding the spine can result in cartilage damage, ligament strain, or persistent low back pain [7][10]. Likewise, an incorrect deadlift posture, including a rounded back or feet positioned too widely or narrowly, can jeopardize spinal integrity and lead to severe musculoskeletal injuries [11]. Despite the known benefits and risks, most online fitness applications continue to present only ideal movement demonstrations, leaving users without real-time guidance to correct dangerous deviations. In recent years, advances in computer vision and machine learning have begun to bridge this gap by enabling automated posture analysis. Frameworks like OpenPose and MediaPipe extract two-dimensional joint landmarks from video streams, while recurrent and convolutional neural networks classify these landmarks into posture categories with growing accuracy [12] [15]. Early implementations provided feedback only after a workout session, limiting their utility for live correction [16][19]. More recent studies have achieved real-time posture evaluation for lower-risk activities such as yoga poses or basic calisthenics delivering instantaneous cues on joint angles and body alignment [13], [14], [18], [20][22]. Yet these systems largely overlook high-load, high-injury-risk powerlifting movements, which introduce additional challenges such as occlusions when the body blocks critical joints and distinct biomechanical phases that standard models often fail to differentiate. To address these limitations, this paper presents a novel real-time posture correction

DOI: https://doi.org/10.62647/IJITCE2025V13I2sPP574-584

service specifically tailored to powerlifting's three cornerstone lifts: bench press, squat, and deadlift. Our approach leverages YOLOv5 for fast, robust detection of the barbell and lifter, combined with MediaPipe's lightweight 3D pose estimation to track joint coordinates at high frame rates. Central to this effort is the newly created PolyView Kinematic Corpus (PKC), which captures synchronized multi-angle video of both concentric and eccentric phases under controlled lighting and camera placements. By training models on PKC's extensive 3D coordinate data, we enable phase-aware posture classification that goes beyond binary "correct/incorrect" judgments, delivering specific feedback on movement quality and muscle engagement in real time. In doing so, we aim to enhance the safety and effectiveness of online powerlifting practice, empowering lifters of all levels to train with confidence and reduce injury risk. The remainder of this paper reviews related work (Section II), details our methodology (Section III), and presents experimental results alongside an analysis of system performance (Section IV)

II. LITERATURE REVIEW

A. Exercise Posture Classification

Early qualitative studies during COVID-19 underscored the need for automated, real-time posture analysis (Kaur et al. [1]). Foundational biomechanical insights for bench press and deadlift form came from Schick et al. [2] and McGuigan and Wilson [3], respectively. Angle-based feature methods appeared in yoga pose classification by Borthakur et al. [4], while Singh et al. [5] combined MediaPipe with Random Forests for bicep curl and shoulder-press stage detection. Chariar et al. [6] used an autoencoder plus Bi-GRU to distinguish seven squat variations, and Gajbhiye et al. [7] fused OpenPose landmarks with SVM/CNN for yoga poses (accuracy > 0.98). Pose Trainer by Chen and Yang [8] applied normalized joint vectors with DTW for binary posture decisions, and Dittakavi et al.'s Pose Tutor [9] added explainability via DenseNet + KNN. Pardos et al. [10] used clustering rules on joint angles for sports exercises, while Redmon et al.'s YOLO [11] revolutionized real-time detection, later adapted for posture tasks. Militaru et al. [12] corrected form using silhouette-based neural nets, and Garg et al. [13] merged CNNs with MediaPipe for robust yoga classification in real settings. De Abreu et al. [14] evaluated commercial fitness apps, finding limited automated feedback, and Shaban [15] documented the home-workout boom, stressing the demand for user-friendly correction tools. Powerlifting–specific injury reviews by Dudagoitia et al. [16], Siewe et al. [17], and Strömbäck et al. [18] informed high-risk exercise criteria, with Schoenfeld [19] detailing squat kinematics foundational to many geometric algorithms. Swain et al. [20] compared deep-learning architectures for yoga landmarks, and Keogh and Winwood [21] surveyed weight-training injury epidemiology, advocating targeted digital feedback.

B. Exercise Posture Evaluation

Liu and Chu [30] used RNNs to provide angle-threshold feedback for lateral raises and curls, while Bonilla et al. [22] proposed general injury guidelines without automated implementation. Büker et al. [23] developed a camera-based quantitative tracking system, and Kanase et al. [24] built a rule-based pose correction pipeline limited to static frames. Wearable-centric real-time coaching emerged in Zhou et al. [25] (two-phase sensor fusion) and Hsiao et al. [26] (deep LSTM + wearables for bench press). Padulo et al. [27] contrasted concentric/eccentric contraction feedback, and Shotton et al. [28] pioneered depth-image pose recognition for live evaluation. Despite these advances, most systems focus on single-joint or low-intensity exercises.

C. Specialized Tools and Datasets

To bolster classifier robustness, several image repositories have been released: Roboflow's Squat-Depth [29] and SDT [23] Datasets, HumonBody1 [24], Faller [25], and Kaggle's Silhouettes of Human Posture [26]. These enable CNN and transformer training under varied conditions. Real-time pipelines leverage Ultralytics' YOLOv5 [30] and benchmark studies comparing YOLOv5, YOLOv8, and YOLOv10, guiding backbone selection.

D. Enhanced Feedback and Evaluation Methods

Temporal fusion and deeper feedback have been explored by Hsiao et al. [26] (LSTM + sEMG) and Zhou et al. [25] (camera + inertial fusion). Padulo et al. [27] provided phase-specific contraction cues, while depth-based approaches (Shotton et al. [28]) and multi-view tracking (Büker et al. [23]) improved spatial precision. Hartley & Zisserman's multi-view geometry principles continue to support 3D reconstruction in posture analysis.

II. PROBLEM STATMENT

The increasing popularity of home-based and online fitness routines, spurred by the COVID-19 pandemic, has raised significant concerns about injury risks

DOI: https://doi.org/10.62647/IJITCE2025V13I2sPP574-584

associated with exercises, particularly high-intensity powerlifting movements such as bench press, back squat, and conventional deadlift [1], [2]. These compound, multi-joint exercises, while effective for building muscle and strength, pose a substantial threat to users when performed with improper form, leading to injuries such as shoulder or wrist damage during bench press, spinal or knee injuries in squats, and back strain or spinal issues in deadlifts [5][9], [17]. Research highlights that improper techniques, excessive training loads, and lack of real-time guidance contribute to elevated injury rates, especially among beginners who often rely on inadequate tools like gym mirrors or costly in-person coaching, increasing their vulnerability when training solo [23], [24]. Current online fitness apps, such as 'Peloton' and 'Perfect Posture & Healthy Back,' provide convenient workout programs and basic posture demonstrations but fail to offer real-time analysis or adaptive feedback to mitigate these risks [3], [4]. Although computer vision tools like MediaPipe and early machine learning approaches have been explored for posture assessment, they are limited by fixed thresholds and lack phase-specific corrections for powerlifting's concentric and eccentric movements, leaving a critical gap in addressing the injury-prone nature of these exercises [12][15]. This underscores the pressing need for an on-device, real-time posture correction system that utilizes YOLOv5 for person detection and machine learning classifiers to deliver precise, user-calibrated feedback, effectively reducing injury risks associated with powerlifting exercises.

EXISTING SYSTEM

The existing system for posture assessment, as seen in tools like Pose Trainer [5], utilizes traditional 2D-based methods to evaluate exercises such as squats, push-ups, lunges, and planks, captured via webcam at 720p and 30 FPS. This approach analyzes biomechanical patterns relevant to powerlifting movements like bench press, squat, and deadlift, noting that improper form reduces effectiveness and heightens injury risk, especially for beginners without professional coaching. Pose Trainer acts as a basic posture aid, but its 2D joint detection limits its ability to detect depth errors in heavy lifts. The workflow starts with video acquisition, standardizing footage to 1280×720 resolution and applying light filtering for lighting consistency, followed by OpenPose processing to detect major joint landmarks shoulders, elbows, hips, and knees producing (x, y) coordinates with confidence scores at 12–15 FPS on a GPU setup. Feature extraction uses geometric trigonometry with arctangent functions to calculate angles like hip–knee–ankle in squats, and Euclidean distance matrices map inter-joint relationships, normalized for user height and camera distance. Posture classification applies heuristic rules to flag deviations (e.g., knee flexion > 110°) and Dynamic Time Warping to align joint angles with expert patterns, achieving about 85% accuracy. However, the feedback module provides only post-session text summaries like "Rep 2: Back not straight during squat," lacking real-time visual overlays or voice guidance, a key limitation for powerlifting where immediate correction is vital.

III. PROPOSED SYSTEM

A. System Architecture

The workflow of this innovative real-time AI posture correction system is depicted in Fig. 1. The process begins with the **PolyView Kinematic Corpus (PKC)**, a specialized dataset featuring 3D joint coordinates extracted from multi-angle videos of individuals performing powerlifting exercises like bench press, squat, and deadlift. Captured using smartphone cameras, these videos include both proper and flawed postures, forming a solid basis for model training. After annotation to pinpoint the exercising individual, the YOLOv5s model is optimized for detection (Fig. 1.1). Video streams from webcams or mobile devices are then processed to identify the primary subject using the trained YOLOv5 model (Fig. 1.2). Following detection, MediaPipe and OpenCV extract 3D joint landmarks, and key angles are calculated using cosine similarity for accuracy, with data normalized via Min-Max scaling (Fig. 1.3). Machine learning and deep learning models, trained on the PKC dataset, classify postures into specific categories six for bench press and eight each for squat and deadlift (Fig. 1.4). Finally, a **Streamlit-based web interface** delivers real-time feedback, analyzing live video to classify postures during exercise phases and providing text, voice instructions, visuals, repetition counts, and angle data (Fig. 1.5).

DOI: https://doi.org/10.62647/IJITCE2025V13I2sPP574-584

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 2s, 2025

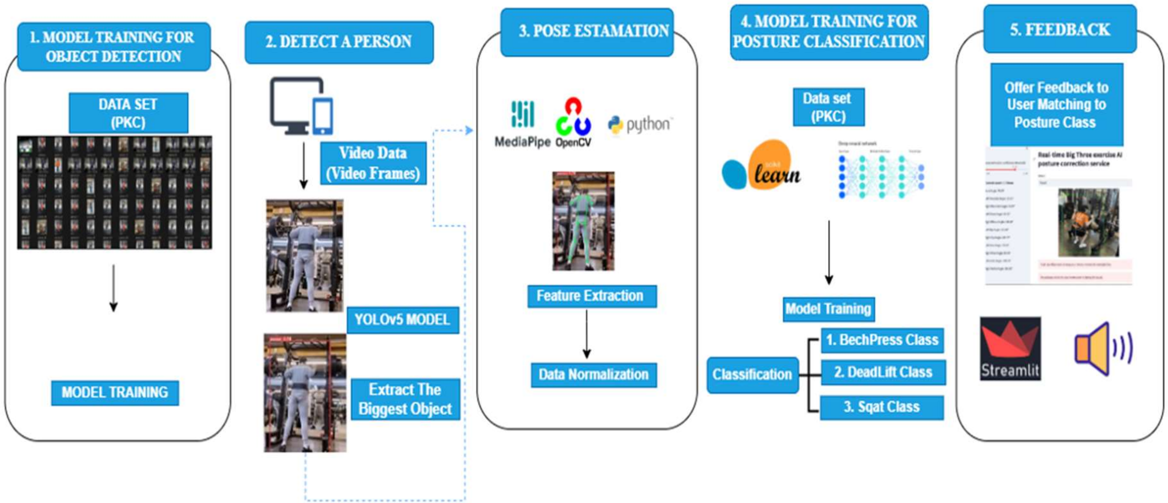

Fig 1: Overall process of the proposed method. The system consists of five main steps: (1) YOLOv5 model for object detection using an exercise dataset, (2) detecting a person in video frames, (3) extracting and normalizing pose data using MediaPipe and OpenCV for pose estimation, (4) training machine learning and deep learning models for posture classification using the (PKC) dataset, and (5) providing real-time feedback to the user through a web interface to correct exercise posture

B. Model Training for Object Detection

This study utilizes the PolyView Kinematic Corpus (PKC), featuring over 5,000 data points from multi-angle videos, to train a robust object detection model for powerlifting exercises, including exercise-specific postures and general poses (e.g., standing, sitting) to boost generalization [23]–[27]. The dataset was annotated to identify the exercising individual, and the lightweight **YOLOv5s** model was chosen for its optimal speed and accuracy in real-time applications [28], [29]. Training employed a batch size of 16 over 200 epochs, with early stopping to prevent overfitting and refine weight selection [11], [30], enabling effective detection of bench press, squat, and deadlift performers across varied settings.

C. Detecting a Person Using YOLOv5

To overcome MediaPipe's single-object limitation, the system uses **YOLOv5** to detect the exercising individual in real-time video streams. The trained model processes each frame, selecting the person with the largest bounding box as the primary subject for posture analysis [31], ensuring accurate targeting in multi-person scenarios and facilitating precise joint landmark extraction and feedback generation [32], [33].

D. Pose Estimation

1) MediaPipe

MediaPipe, an open-source Google framework, is used for real-time pose estimation due to its efficiency and accuracy [32]. This study employs version 0.8.9, optimized for resource-limited devices like phones and laptops, outperforming OpenPose's computational demands by detecting 33 body landmarks for precise angle calculations [33], [34]. Its adaptability to lighting, angles, and distances, plus cross-platform support, suits this application [35]. A confidence threshold of 0.7 reduces false positives, processing frames at over 35 FPS faster than OpenPose's 15 FPS ideal for powerlifting feedback [32], [36].

2) Feature Extraction

We extract 3D joint coordinates and angles for posture analysis. Coordinates as (x, y, z) vectors from 33 MediaPipe landmarks via webcam form the base vector, while angles derived from these landmarks enhance classification [16], [17]. Recent yoga studies show combining coordinates and 11 key angles in machine learning models improves accuracy [17], a method we adopt (see Table 1 for landmark details and Fig 2 for landmark map).

Joint Angle Calculation

Joint angles, critical for posture checks, use 33 landmarks (e.g., 11, 12 for shoulders [36]). Table 1 lists landmarks for angles at neck, shoulders, elbows,

DOI: https://doi.org/10.62647/IJITCE2025V13I2sPP574-584

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 2s, 2025

hips, knees, and ankles. For example, the left shoulder angle uses landmarks 13, 11, and 23, while elbows use shoulder, elbow, and wrist points. With $p_i = (x_i, y_i, z_i)$ the angle at B (between A, B, C) for bench press is:

$$\theta_{\text{deg}} = \left| \cos^{-1}\left(\frac{\overrightarrow{BA} \cdot \overrightarrow{BC}}{|\overrightarrow{BA}||\overrightarrow{BC}|}\right) \times \frac{180.0^\circ}{\pi} \right| \quad (1)$$

Algorithm 1 ensures angles are 0°–180°, with Streamlit visualizing feedback (see Fig 3 for angle calculation).

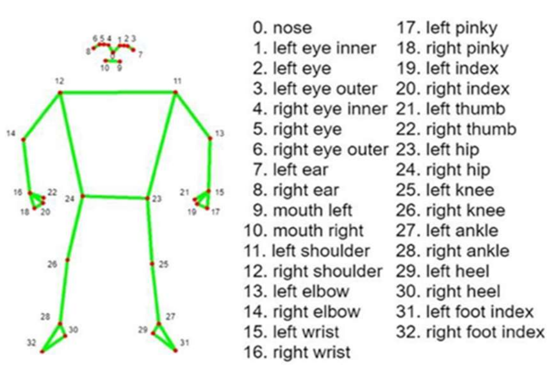

Fig 2: List of the joint land marks

Fig 3: Joint Angle Calculation: Illustration of the method used to calculate joint angles between landmarks A, B, and C for evaluating posture correctness during exercises

3) Data Normalization

MediaPipe provides 3D landmarks from PKC videos $p_i = (x_i, y_i, z_i)$ with visibility scores [0,1][32]. Coordinates are normalized to $[-1,1]$[33], and OpenCV labels postures for missing data due to quality issues [38]. Visibility $pi \mid vi \geq 0.6$ (2) filters data, excluding noisy videos. Angles, calculated via cosine similarity, are Min-Max scaled to [0, 1] using:

$$\theta' = \frac{\theta - \theta_{\min}}{\theta_{\max} - \theta_{\min}} \quad (3)$$

for uniform learning, visualized in Streamlit [37], [39].

Table 1: The joint landmarks used to calculate the angles between key joints

Angle	Position	Joint landmark numbers	Explanation
Neck	Left	11, 0, 23 (left shoulder, nose, left hip)	The neck angle is computed as the arithmetic mean of two angles: one formed by the landmarks of the left shoulder, nose, and left hip, and the other by the right shoulder, nose, and right hip. This method ensures symmetric evaluation of the neck joint.
	Right	12, 0, 24 (right shoulder, nose, right hip)	
Shoulder	Left	13, 11, 23 (left elbow, left shoulder, left hip)	The shoulder angle is calculated separately for the left and right sides using three key landmarks: the elbow, shoulder, and hip. These angles represent the relative alignment of the upper body.
	Right	14, 12, 24 (right elbow, right shoulder, right hip)	
Elbow	Left	11, 13, 15 (left shoulder, left elbow, left wrist)	The elbow angle is computed by using three points: the shoulder, elbow, and wrist on each side. This reflects the bending of the arm.
	Right	12, 14, 16 (right shoulder, right elbow, right wrist)	
Hip	Left	11, 23, 25 (left shoulder, left hip, left knee)	The hip angle is measured by the relative positions of the shoulder, hip, and knee, providing insight into lower body alignment.
	Right	12, 24, 26 (right shoulder, right hip, right knee)	
Knee	Left	23, 25, 27 (left hip, left knee, left ankle)	The knee angle is calculated using the landmarks of the hip, knee, and ankle to assess knee joint movement.
	Right	24, 26, 28 (right hip, right knee, right ankle)	
Ankle	Left	25, 27, 29 (left knee, left ankle, left heel)	The ankle angle is computed by considering the knee, ankle, and heel, which captures foot positioning and lower leg alignment.
	Right	26, 28, 30 (right knee, right ankle, right heel)	

E) Model Training for Enhanced Posture Classification

1) Data Gathering

Building on Table 2, prior methods have limitations [14], [22], [37], [38]. Wearables in [37], [38] offer detail but are costly and restrictive, while [22]'s static images suit planks/squats but miss dynamic phases like deadlifts. [14]'s MediaPipe video approach avoids wearables but ignores eccentric/concentric distinctions [39], critical for phase-specific stress. Our multi-view setup (200 cm front, 180 cm at 45° diagonals) captures occluded joints (see Fig 4).

Leveraging MediaPipe for Dynamic Posture Data Collection

Like [14], we use MediaPipe for its open-source, attachment-free design, enabling natural movement in bench press, squat, and deadlift, capturing both contraction phases for nuanced insights and accurate repetition counting [39].

Building a Comprehensive Dataset with PKC

PKC, a multi-angle dataset for bench press, squat, and deadlift, includes 3,023 samples (Table 2) from a five-year expert using an iPhone 13 Pro, labeled with OpenCV, capturing both phases for injury research (see Table 4).

DOI: https://doi.org/10.62647/IJITCE2025V13I2sPP574-584

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 2s, 2025

Optimizing Joint Landmark Recognition Through Multi-Angle Filming

Multi-angle filming at 200 cm front and 180 cm diagonals minimizes occlusions, enhancing joint visibility (see Fig 5).

Study	# Classes	Total Samples	Method of Data Collection	Type of Exercise	Ecc./Con.
Hsiao et al. [37]	12	Not disclosed	Wearable devices	Bench press	X
Zhou et al. [38]	9	1,700	Wearable devices	Dumbbell curl, Bent-over row, Bench press, Lying triceps extension, Front raise, Lateral raise, Shoulder press, Overhead triceps extension, Cable crossover	X
Militaru et al. [22]	6	2,400	Static images	Plank, Squat	X
Chariar et al. [14]	7	1,332	Joint information collected through MediaPipe from exercise videos	Squat	X
Ours (PKC)	22	3,023	Joint information collected through MediaPipe from exercise videos	Bench press, Squat, Deadlift	O

Table 2: Comparison of data collection methods used in previous studies.

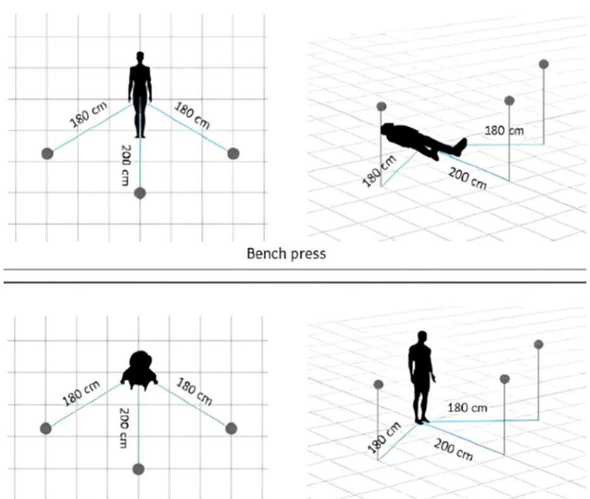

Fig:4 Camera Setup for Data Collection: Camera positions used forcapturing exercise movements during bench press, squat, and deadlift.Cameras are placed 200 cm in front and 180 cm at diagonal angles toensure comprehensive joint landmark detection.

Enhancing Pose Estimation with Multi-View Geometry

Multi-view geometry reconstructs 3D landmarks [42], aligning points across cameras to address occlusions, with 200 cm front and 180 cm 45° angles ensuring joint coverage.

2) Model Training

Posture models use machine learning algorithms for bench press, squat, and deadlift. Data were cleaned, merged, and standardized, split into 70% training and 30% testing with a fixed seed. StandardScaler normalized features, and four pipelines with $LogisticRegression\ (C: 0.01, 0.1, 1, 10)$, $RidgeClassifier(\alpha: 0.1,1,10)$, RandomForestClassifier$n_estimators: 100, 200, 500,$ $max_{dept}\ None, 10,20,$ $min_{\{samples_{leaf}:1,2,5)}$, and GradientBoostingClassifier $(depth = 3,$ $learning\_rate: 0.01, 0.1, n\_\{estimators\}$ $: 100, 200)$ were evaluated via 5-fold cross-validation for F1 scores. Test results showed $F1 \approx$ $0.80, 0.83, 0.88, and\ 0.91$, respectively, with RandomForestClassifier selected for its precision and recall.

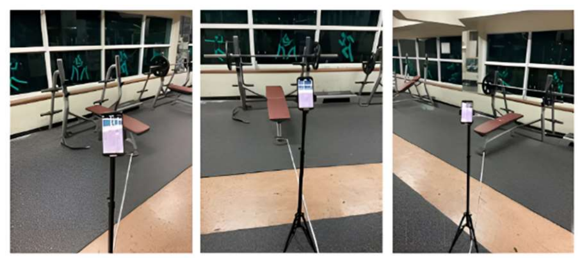

Fig 5: Shooting Stand Position for Bench Press Data Collection Example of the shooting stand setup positioned at left diagonal, front,and right diagonal locations, 200 cm and 180 cm away, respectively, forcapturing bench press exercise movements

F. Posture Inference and Correction Algorithm for Each Exercise

This study advances beyond basic correct/incorrect classification by providing detailed, exercise-specific feedback to prevent injuries and enhance lifting technique, unlike existing systems relying on binary classifiers or fixed angle thresholds. Our approach identifies multiple error modes for bench press, squat, and deadlift, delivering nuanced cues based on joint angle deviations from optimal references (see Table 3). A real-time vision pipeline captures 3D joint landmarks, overlaying a live skeletal visualization and annotating key angles, with adjustable confidence thresholds for varying camera conditions. Frame classification computes angular deviation as:

$$\boldsymbol{\Delta\theta} = \boldsymbol{\theta}_{\text{actual}} - \boldsymbol{\theta}_{\text{reference}}$$

DOI: https://doi.org/10.62647/IJITCE2025V13I2sPP574-584

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 2s, 2025

where a positive $\Delta\boldsymbol{\theta}$ suggests reducing the angle, and a negative value recommends increasing it. Collaborating with three certified trainers (each >3 years' experience), we defined injury-prone faults. For bench press, categories include Correct Posture,

Type of Exercise	Muscle Contraction Phase	Posture Classification	Exercise Posture Classes	Number of Data Samples
Bench press	Concentric Contraction (up)	Correct Posture	b_correct_up	134
		Excessive Arch in Lower Back	b_excessive_arch_up	173
		Arms Spread Too Wide	b_arms_spread_up	153
	Eccentric Contraction (down)	Correct Posture	b_correct_down	147
		Excessive Arch in Lower Back	b_excessive_arch_down	167
		Arms Spread Too Wide	b_arms_spread_down	181
Squat	Concentric Contraction (up)	Correct Posture	s_correct_up	118
		Non-neutral Spine	s_spine_neutral_up	113
		Knees Caved In	s_caved_in_knees_up	114
		Feet Spread Too Wide	s_feet_spread_up	120
	Eccentric Contraction (down)	Correct Posture	s_correct_down	115
		Non-neutral Spine	s_spine_neutral_down	117
		Knees Caved In	s_caved_in_knees_down	113
		Feet Spread Too Wide	s_feet_spread_down	118
Deadlift	Concentric Contraction (up)	Correct Posture	d_correct_up	138
		Non-neutral Spine	d_spine_neutral_up	139
		Arms Spread Too Wide	d_arms_spread_up	141
		Arms Too Narrow	d_arms_narrow_up	151
	Eccentric Contraction (down)	Correct Posture	d_correct_down	132
		Non-neutral Spine	d_spine_neutral_down	152
		Arms Spread Too Wide	d_arms_spread_down	139
		Arms Too Narrow	d_arms_narrow_down	148

Table 3: Classification of postures across muscle contraction phases for powerlifting exercises.

Excessive Lower Back Arch, Grip Too Wide, and Grip Too Narrow; e.g., an excessive arch triggers "Reduce lumbar arch" (see Fig 6). For squats, faults like Knee Valgus, Insufficient Depth, Non-Neutral Spine, and Stance Too Wide/Narrow are addressed with "Push hips back" or "Drive knees outward" (see Fig 7). Deadlift errors Spinal Rounding, Bar Too Far, and Knees Locked Too Early prompt "Keep chest up" or "Drag barbell close" (see Fig 8). This trainer-validated, deviation-based feedback refines biomechanics, reduces injury risk, and optimizes training.

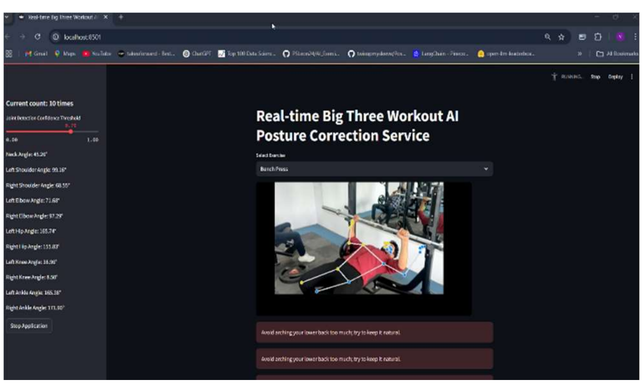

Fig 6: Real-Time Bench Press Posture Feedback. Example of real-time AI feedback for bench press posture correction, demonstrating the detected issues such as excessive lower back arching and providing corrective suggestion

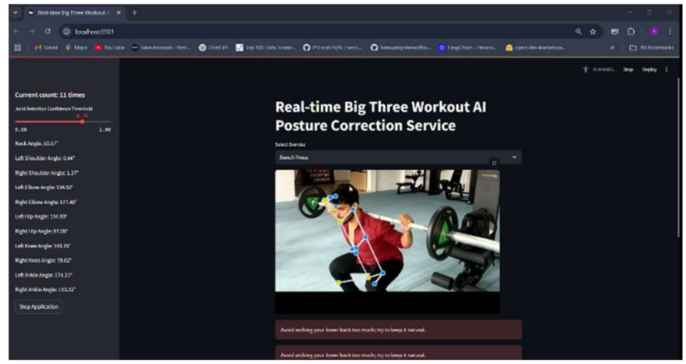

Fig 7: Real-Time Squat Posture Feedback: Example of real-time AI feedback for squat posture correction, showing detected issues such as non-neutral spine and knees caving in, along with corrective suggestions

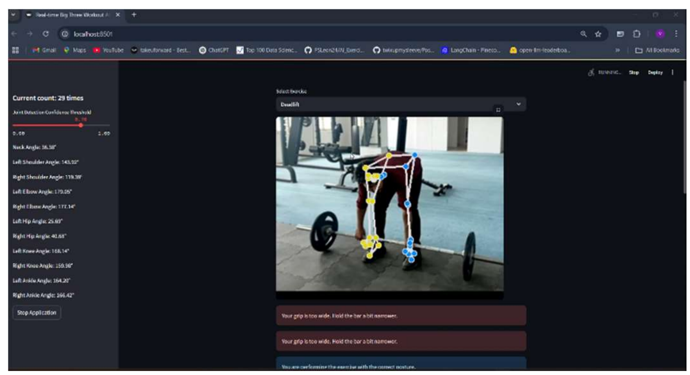

Fig 8: Real-Time Deadlift Posture Feedback: Example of real-time AI feedback for deadlift posture correction, indicating correct posture and providing suggestions for improving grip width.

IV. Performance Evaluation Overview

This section provides a detailed assessment of models developed for real-time AI posture correction in powerlifting exercises, focusing on their effectiveness for bench press, squat, and deadlift movements. It includes implemented models, experimental setup, performance evaluation using machine learning classifiers and **YOLOv5**, and a flowchart of the input processing pipeline (see Fig 9). The flowchart illustrates the flow from input data (joint landmarks 0–32 and angles) through combination into input embeddings, transformation via a transform encoder into embedding vectors, and classification by an ML

DOI: https://doi.org/10.62647/IJITCE2025V13I2sPP574-584

ISSN 2347–3657

Volume 13, Issue 2s, 2025

classifier to determine the class, enhancing the understanding of data processing.

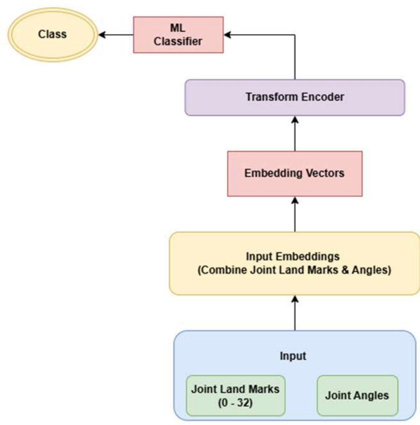

Fig 9: This study presents the flow diagram of the Transformer-based posture classifier, showing the process from input embedding of joint landmarks and angles through a Transform Encoder to an ML Classifier for real-time posture assessment in powerlifting exercises.

Summary of Implemented Models

Our study emphasizes effective object detection and posture classification, using **YOLOv5** for detection and machine learning classifiers, with details in Table 5. We improved the dataset with labeling methods to enhance MediaPipe's pose estimation accuracy, then optimized **YOLOv5** configurations (batch size 16, 200 epochs, yolov5s.pt weights) for equipment detection. The second experiment evaluated classifiers logistic regression ($C\ tuned$ $100 iterations$), ridge classification ($\alpha\ at$ 0.1,1,10), random forest (100 trees, no max depth), and gradient boosting (100 trees, depth 3, learning rate 0.1) to capture posture nuances.

Ex		Parameters	
Ex. 1	Exercise Object Detection Model Using YOLOv5	batch size	16
		epochs	200
		weights	yolov5s.pt
Ex. 2	Exercise Posture Classification Model Using Machine Learning Algorithms	Logistic Regression	C = 1.0
			max_iter = 100
		Ridge Classifier	alpha = 1.0
		Random Forest	n_estimators = 100
			max_depth = None
		Gradient Boosting	n_estimators = 100
			max_depth = 3
			learning_rate = 0.1

Table 5: Summarized information of the implemented models.

Experimental Environment Setup

The setup included a server with Windows 11 Pro, a 13th Gen Intel Core i7 at 3.50 GHz, GeForce RTX 4060, and 16 GB RAM, plus a MacBook (macOS 14, M1 chip) and iPhone 13 Pro for data capture, ensuring computational flexibility. Python 3.10 supported **YOLOv5** and machine learning libraries. The PolyView Kinematic Corpus (PKC) dataset was split 7:3, with 668/287 (bench press), 649/279 (squat), and 798/342 (deadlift) samples for balanced training and testing.

Model Performance Evaluation with Metrics

We assessed posture classification and **YOLOv5** object detection using accuracy, precision, recall, F1-score, and mAP. Accuracy is

$$A = \frac{T_p + T_n}{T_p + T_n + F_p + F_n},$$

Precision is

$$P = \frac{T_p}{T_p + F_p}$$

Recall is

$$R = \frac{T_p}{T_p + F_n}$$

, and F1-score is

$$F1 = \frac{2 \cdot P \cdot R}{P + R}$$

evaluating performance on imbalanced data.

$$, mAP = \frac{1}{N} \sum_{i=1}^{N} AP_i ,$$

measures detection across classes. These metrics, applied to PKC-trained models, ensure robust real-time correction.

V. Performance Evaluation Results of Ml Models

In this Section we are Evaulating the Ml Models Figure 10 illustrates the classification metrics for the bench-press dataset. Here, Logistic Regression and Ridge Classifier achieve respectable performance with accuracy, precision, recall, and F_1-score of 0.993 and 0.979, respectively, while both Random Forest and Gradient Boosting attain near-perfect scores of 0.997

DOI: https://doi.org/10.62647/IJITCE2025V13I2sPP574-584

ISSN 2347–3657

Volume 13, Issue 2s, 2025

across all measures. Figure 11 presents the squat results: Logistic Regression records 99.3 % on each metric, Ridge Classifier improves slightly to 99.6 %, and both Random Forest and Gradient Boosting demonstrate flawless classification with perfect 1.000 values. By contrast, the deadlift outcomes shown in Figure 12 reveal that linear models lag behind Logistic Regression and Ridge Classifier reach only around 0.883 and 0.874 on each metric whereas Random Forest excels at 98.3 % and Gradient Boosting closely follows at 96.8 %, underscoring the clear advantage of ensemble tree-based methods for detecting subtle deadlift postures.

Bench press	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.993	0.993	0.993	0.993
Ridge Classifier	0.979	0.979	0.979	0.979
Random Forest	**0.997**	**0.997**	**0.997**	**0.997**
Gradient Boosting	**0.997**	**0.997**	**0.997**	**0.997**

Fig 10: Performance comparison of bench press posture classification models implemented using machine learning algorithms (The best performance is marked in bold)

Squat	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.993	0.993	0.993	0.993
Ridge Classifier	0.996	0.997	0.996	0.996
Random Forest	**1.000**	**1.000**	**1.000**	**1.000**
Gradient Boosting	**1.000**	**1.000**	**1.000**	**1.000**

Fig 11: Performance comparison of Squat posture classification models implemented using machine learning algorithms (The best performance is marked in bold)

Deadlift	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.883	0.884	0.883	0.883
Ridge Classifier	0.874	0.876	0.874	0.874
Random Forest	**0.983**	**0.983**	**0.983**	**0.983**
Gradient Boosting	0.968	0.968	0.968	0.968

Fig 12: Performance comparison of deadlift posture classification models implemented using machine learning algorithms (The best performance is marked in bold)

Conclusion

In this work, we leveraged MediaPipe's real-time pose estimation to extract joint landmarks and key angles from our custom PKC dataset, then trained only traditional machine-learning classifiers to detect correct versus incorrect form for bench press, squat, and deadlift. The models were deployed in a web browser using OpenCV and Streamlit, combined with YOLOv5 person detection to isolate the exerciser and improve landmark accuracy. During live sessions, the system analyses each frame, classifies the posture, and uses text-to-speech feedback to alert users to any errors, all on standard CPU-only hardware. By relying solely on traditional classifiers, our approach remains lightweight and interpretable while still delivering accurate, frame-wise corrections. Future work will expand PKC to include more diverse participants and investigate integrating surface EMG signals to assess muscle activation alongside postural analysis

REFERENCES:

[1] H. Kaur, T. Singh, Y. K. Arya, and S. Mittal, "Physical fitness and exercise during the COVID-19 pandemic: A qualitative enquiry," Front. Psychol., vol. 11, Oct. 2020, Art. no. 590172.

[2] E. E. Schick, J. W. Coburn, L. E. Brown, D. A. Judelson, A. V. Khamoui, T. T. Tran, and B. P. Uribe, "A comparison of muscle activation between a Smith machine and free-weight bench press," J. Strength Cond. Res., vol. 24, no. 3, pp. 779–784, 2010.

[3] M. R. M. McGuigan and B. D. Wilson, "Biomechanical analysis of the deadlift," J. Strength Cond. Res., vol. 10, no. 4, pp. 250–255, 1996.

[4] D. Borthakur, A. Paul, D. Kapil, and M. J. Saikia, "Yoga pose estimation using angle-based feature extraction," Healthcare, vol. 11, no. 24, p. 3133, Dec. 2023.

[5] V. Singh, A. Patade, G. Pawar, and D. Hadsul, "TrAIner An AI fitness coach solution," in Proc. IEEE 7th Int. Conf. Converg. Technol. (I2CT), Mumbai, India, Apr. 2022, pp. 1–4.

[6] M. Chariar, S. Rao, A. Irani, S. Suresh, and C. S. Asha, "AI Trainer: Autoencoder-based approach for squat analysis and correction," IEEE Access, vol. 11, pp. 107135–107149, 2023.

DOI: https://doi.org/10.62647/IJITCE2025V13I2sPP574-584

International Journal of
Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 2s, 2025

[7] R. Gajbhiye, V. Chawla, and A. Singh, "AI human-pose estimation: Yoga-pose detection and correction," Int. J. Innov. Sci. Res. Technol., vol. 7, no. 5, pp. 1649–1658, 2022.

[8] S. Chen and R. R. Yang, "Pose Trainer: Correcting exercise posture using pose estimation," arXiv:2006.11718, 2020.

[9] B. Dittakavi, D. Bavikadi, S. V. Desai, S. Chakraborty, N. Reddy, V. N. Balasubramanian, B. Callepalli, and A. Sharma, "Pose Tutor: An explainable system for pose correction in the wild," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops, Jun. 2022, pp. 3539–3548.

[10] A. Pardos, M. Tziomaka, A. Menychtas, and I. Maglogiannis, "Automated posture analysis for the assessment of sports exercises," in Proc. 12th Hellenic Conf. Artif. Intell., Sep. 2022, pp. 1–9.

[11] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, real-time object detection," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2016, pp. 779–788.

[12] C. Militaru, M.-D. Militaru, and K.-I. Benta, "Physical exercise-form correction using neural networks," in Companion Proc. Int. Conf. Multimodal Interact., Oct. 2020, pp. 240–244.

[13] S. Garg, A. Saxena, and R. Gupta, "Yoga-pose classification: A CNN and MediaPipe-inspired deep-learning approach for real-world application," J. Ambient Intell. Humanized Comput., vol. 14, no. 12, pp. 16551–16562, Dec. 2023.

[14] J. M. de Abreu, R. A. de Souza, L. G. Viana-Meireles, J. Landeira-Fernandez, and A. Filgueiras, "Effects of physical activity and exercise on well-being in the context of the COVID-19 pandemic," PLoS ONE, vol. 17, no. 1, Jan. 2022, Art. no. e0260465.

[15] H. Shaban, "The pandemic's home-workout revolution may be here to stay," The Washington Post, Jan. 2021.

[16] E. Dudagoitia, A. García-De-Alcaraz, and L. L. Andersen, "Safety of powerlifting: A literature review," Sci. Sports, vol. 36, no. 3, pp. 59–68, Jun. 2021.

[17] J. Siewe, J. Rudat, M. Röllinghoff, U. J. Schlegel, P. Eysel, and J. W.-P. Michael, "Injuries and overuse syndromes in powerlifting," Int. J. Sports Med., vol. 32, no. 9, pp. 703–711, Sep. 2011.

[18] E. Strömbäck, U. Aasa, K. Gilenstam, and L. Berglund, "Prevalence and consequences of injuries in powerlifting: A cross-sectional study," Orthop. J. Sports Med., vol. 6, no. 5, May 2018, Art. no. 2325967118771016.

[19] B. J. Schoenfeld, "Squatting kinematics and kinetics and their application to exercise performance," J. Strength Cond. Res., vol. 24, no. 12, pp. 3497–3506, 2010.

[20] J. Swain, P. Roy, and S. Mukherjee, "Deep-learning models for yoga-pose monitoring," Algorithms, vol. 15, no. 11, p. 403, 2022.

[21] J. W. L. Keogh and P. W. Winwood, "The epidemiology of injuries across weight-training sports," Sports Med., vol. 47, no. 3, pp. 479–501, Mar. 2017.

[22] D. A. Bonilla, L. A. Cardozo, J. M. Vélez-Gutiérrez, A. Arévalo-Rodríguez, S. Vargas-Molina, J. R. Stout, R. B. Kreider, and J. L. Petro, "Exercise selection and common injuries in fitness centers: A systematic integrative review and practical recommendations," Int. J. Environ. Res. Public Health, vol. 19, no. 19, p. 12710, Oct. 2022.

[23] "Squat-Depth Image Dataset," Roboflow, accessed Sep. 10, 2023.

[24] "SDT Image Dataset," Roboflow, accessed Sep. 10, 2023.

[25] "HumonBody1 Computer Vision Project," Roboflow, accessed Sep. 10, 2023.

[26] "Faller Image Dataset," Roboflow, accessed Sep. 10, 2023.

[27] "Silhouettes of Human Posture," Kaggle, accessed Sep. 14, 2023.

[28] J. Redmon et al., "You Only Look Once: Unified, real-time object detection," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2016, pp. 779–788.

[29] Ultralytics, YOLOv5, accessed Jul. 1, 2024.

[30] E. Casas, L. Ramos, E. Bendek, and F. Rivas-Echeverría, "YOLOv5 vs. YOLOv8: Performance benchmarking in wildfire and smoke detection scenarios," J. Image Graph., vol. 12, no. 2, pp. 127–136, 2024.

[31] Mr. Pathan Ahmed Khan, Dr. M.A Bari,: Impact Of Emergence With Robotics At Educational Institution And Emerging Challenges", International Journal of Multidisciplinary Engineering in Current Research(IJMEC), ISSN: 2456-4265, Volume 6, Issue 12, December 2021,Page 43-46

DOI: https://doi.org/10.62647/IJITCE2025V13I2sPP574-584

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 2s, 2025

[32] Shahanawaj Ahamad, Mohammed Abdul Bari, Big Data Processing Model for Smart City Design: A Systematic Review ", VOL 2021: ISSUE 08 IS SN : 0011-9342 ;Design Engineering (Toronto) Elsevier SCI Oct : 021;Q4 Journal

[33] M.A.Bari & Shahanawaj Ahamad, "Object Identification for Renovation of Legacy Code", in International Journal of Research and Reviews in Computer Science (IJRRCS),ISSN:2079-2557,Vol:2,No:3,pp:769-773,Hertfordshire,U.K., June 2011

DOI: https://doi.org/10.62647/IJITCE2025V13I2sPP574-584