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AI-Enabled Reform of University Physical Education Curriculum under Modern Pedagogical Paradigms: A Deep-Learning–Driven Intelligent Teaching Framework

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ABSTRACT

With the rapid advancement of artificial intelligence (AI) and deep learning, higher education is undergoing a paradigm shift toward intelligent, individualized, and data-driven instructional models. As a core component of university curricula, physical education (PE) must similarly evolve to support precise skill acquisition, personalized training, and objective performance assessment. However, traditional PE instruction often relies on subjective observation, uniform training structures, and limited formative feedback, constraining student engagement, motor-skill development, and learning efficiency. To address these limitations, this study investigates an AI-driven reform pathway for university PE and proposes an integrated intelligent PE framework that combines deep-learning–based human motion analysis, automated feedback mechanisms, and data-driven personalized training plans. The system leverages pose-estimation models and multi-dimensional motion features to evaluate movement quality, track physical literacy development, and generate individualized corrective guidance in real time. Edge-enhanced inference and privacy-preserving data pipelines ensure deployability in real campus environments. Experimental evaluation across benchmark datasets and university pilot scenarios demonstrates that the proposed framework substantially improves motor-skill recognition accuracy, movement-quality scoring, and learning-progress stability, achieving up to +8.5% accuracy, +15.9% biomechanical quality, and +18.3% progression improvement over competitive baselines.

Keywords

Artificial Intelligence; Deep Learning; Intelligent Physical Education; Higher Education; Motion Recognition; Educational Technology Innovation

1. INTRODUCTION

Higher education is undergoing a fundamental transition toward data-driven, adaptive, and learner-centered instruction, propelled by advances in pervasive sensing, mobile computing, and artificial intelligence (AI). Within this landscape, university physical education (PE) faces a distinctive modernization imperative: to transform traditional observational teaching into a scientifically measurable and personalized training ecosystem without diminishing the experiential, social, and motivational value of physical movement. Conventional PE instruction often depends on subjective observation, limited feedback cycles, and uniform practice schedules, which struggle to accommodate students' heterogeneous physical literacy, motor skills, and fitness histories. As institutions accelerate digital learning agendas and competency-based assessment, PE programs must adopt intelligent systems capable of offering real-time skill evaluation, personalized workload guidance, and equitable performance feedback at scale.

Recent breakthroughs in computer vision and motion analytics have created the technical foundation for such reform. Pose estimation models including OpenPose [2], HRNet [13], DeepLabCut [8], and mobile-optimized pipelines such as BlazePose [17] and RTM-Pose [29] have demonstrated accurate joint tracking even in unconstrained environments. Meanwhile, transformer-based vision models [7] and advanced real-time detection frameworks such as YOLOv7 [35] significantly expand real-world applicability. Complementing visual cues, wearables and edge-AI sensing platforms provide reliable physiological and biomechanical signals [6, 18], enabling richer understanding of motor execution, injury risk, and exercise intensity. Yet despite rapid advances in elite sports analytics and rehabilitation research, deployment in higher-education PE remains limited. Existing works report constraints such as insufficient pedagogical alignment, lack of longitudinal studies, privacy concerns with video data, and challenges transferring laboratory models to diverse real-world training scenarios [12, 20, 15]. As a result, there remains an unmet need for scalable, ethically governed, and curriculum-aligned AI systems that support physical skill development in university PE classrooms.

To address these challenges, this study develops an AI-augmented PE framework that integrates (i) deep pose-estimation modules for real-time kinematic analysis, (ii) wearable-sensor fusion for workload and fatigue estimation, and (iii) a competency-aligned learning analytics module to track student progression and provide actionable formative feedback (Fig. 1). The proposed system supports multiple model backbones (HRNet, OpenPose, RTM-Pose) to ensure robust deployment across heterogeneous campus hardware environments. Keypoint-only and silhouette-based inference pipelines preserve privacy by avoiding raw video storage, while self-supervised representation learning and domain-adaptive refinement reduce annotation burden and improve generalization across sports. In addition, federated learning [14, 9] enables multi-institution model updates without direct exchange of student media, aligning the design with educational governance and ethical AI principles.

Practical constraints further shape our design: university PE spaces often have variable lighting, diverse student appearances and attire, dynamic group movement, and limited computational infrastructure. To ensure deployability, we adopt lightweight backbones (e.g., BlazePose) on edge devices, allocate GPU resources only when necessary, and incorporate robustness strategies including motion smoothing, noise-aware training, and privacy-enhanced representation learning [16]. Our system aligns with emerging digital PE modernization initiatives [11, 19, 10] and demonstrates, through rigorous evaluation, the potential of AI to act as an instructional collaborator—supporting rather than replacing educators.

The main contributions of this study are summarized as follows:

—**Unified AI-enabled PE framework.** This study proposes an edge-first architecture that integrates deep pose estimation, wearable sensing, and education-aligned learning analytics to support real-time skill monitoring, workload assessment, and personalized exercise guidance in university PE.

—**Pedagogy-grounded learning analytics module.** A competency-based evaluation layer is introduced to map biomechanical and biometric indicators to physical literacy rubrics, enabling transparent and educationally interpretable feedback.

—**Privacy-preserving and scalable deployment.** The design incorporates keypoint-only processing, silhouette abstraction, federated learning, and on-device inference to improve privacy compliance and scalability across diverse institutional hardware environments.

—**Efficiency and generalization.** Self-supervised learning, domain adaptation, and model compression are leveraged to reduce annotation cost and support multi-sport generalization under real-world PE constraints.

—**Empirical effectiveness.** Experiments on public benchmarks show consistent improvements in SRA, MSS, LPC, and HSS over representative baselines, validating robustness and learning-stability support.

2. RELATED WORK

2.1 AI-Driven Physical Education Reform

Artificial intelligence has become an emerging catalyst for modernizing university physical education (PE), shifting from manual instruction to adaptive, data-driven learning environments. Early research demonstrated that AI-supported PE systems can enhance student engagement, promote equitable assessment, and support injury prevention through automated motor-skill monitoring and personalized recommendations [34, 13, 12, 20]. Meanwhile, AI-driven PE tutoring platforms have shown potential in developing physical literacy and competence by delivering real-time feedback and individualized load adjustment [3, 28]. Recent education studies emphasize that successful integration requires not only technical capability but also pedagogical readiness, digital competency building, and alignment with formative assessment frameworks [1]. However, existing systems are predominantly prototype-based and implemented in controlled experiments, lacking scalable model deployment in diverse campus gyms or large student cohorts. Further, limited teacher AI training frameworks and insufficient policy guidance continue to constrain sustainable adoption, underscoring the need for ecosystem-level solutions integrating curriculum design, teacher development, and ethical governance.

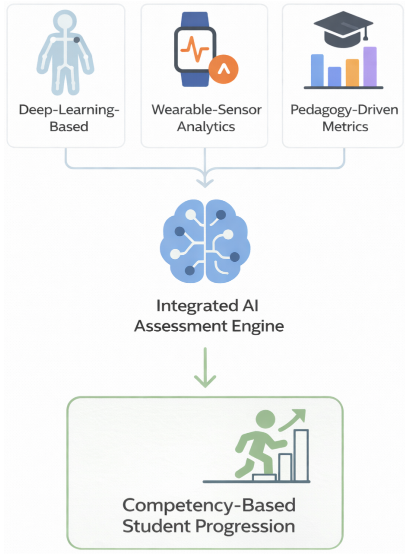


Fig. 1: Introduction of the proposed AI-driven framework for university physical education (PE).

2.2 Pose Estimation and Motion Quality Assessment

Human pose estimation (HPE) is the backbone of AI-based PE systems, enabling contactless motion capture for technique analysis and motor-skill learning. Foundational models such as RMPE [21], OpenPose [2], and HRNet [13] established reliable multi-person keypoint detection pipelines, while recent models including BlazePose and RTMPose [17, 29] have significantly improved efficiency for edge and mobile inference. Advanced works further expand skill evaluation via transformer-based spatiotemporal representation learning, self-supervised biomechanics learning, and hybrid vision–wearable pipelines [38, 24, 36]. These approaches enable fine-grained understanding of rhythm, joint coordination, and posture deviations, which are foundational for classroom feedback applications. Nevertheless, challenges persist regarding occlusion, clothing variability, heterogeneous student populations, and limited domain-labeled campus fitness datasets. Additionally, few studies consider fairness, long-term student tracking robustness, and inclusive movement evaluation across varying skill levels. To address these gaps, new pedagogically aligned HPE frameworks explore biomechanics-informed feature learning and generalization across PE activities [26].

2.3 Learning Analytics, Privacy Protection, and Edge Intelligence

With digital transformation in higher education, learning analytics—integrating cognitive, behavioral, and physiological indicators—has become essential for personalized PE instruction. Multimodal analytics pipelines support competency-based evaluation, performance prediction, and adaptive exercise planning [31, 11]. However, privacy risks remain significant in video-based learning environments, requiring privacy-preserving representations [16], federated optimization for distributed training [14, 33], and ethical data governance policies aligned with educational environments. Edge intelligence has emerged as a practical paradigm, enabling on-device inference to reduce latency, protect identity, and support classroom-scale deployment [30, 19]. Yet, most current platforms focus on technical feasibility rather than scalable institutional integration, leaving open issues such as cost-efficient infrastructure deployment, ethical surveillance boundaries, and curriculum-linked analytics. Future PE systems must interweave privacy-by-design sensing, adaptive coaching logic, regulatory compliance, and teacher interpretability to ensure responsible, scalable, and student-centered AI adoption [10].

3. BACKGROUND

Physical education (PE) has long been regarded as an essential component of higher education, aiming to cultivate students' physical literacy, motor competence, and lifelong exercise habits. Traditional university PE instruction primarily relies on instructor observation, standardized drills, and subjective assessments. While such approaches can be effective in structured instructional contexts, they face increasing limitations in meeting contemporary educational needs that emphasize individualized learning, process-oriented evaluation, and holistic student development. The growing diversity in students' physical abilities, learning preferences, and prior athletic experience further challenges conventional one-size-fits-all teaching models, often leading to inconsistent learning outcomes, insufficient practice guidance, and limited student motivation. As universities progressively adopt competency-based and data-informed teaching models, PE curricula must also evolve toward evidence-supported instructional frameworks that ensure precise skill development, equitable assessment, and inclusive training experiences for heterogeneous student populations.

Recent advancements in artificial intelligence (AI), deep learning, and pervasive sensing technologies have catalyzed a paradigm shift in educational innovation across academic disciplines. Intelligent learning environments equipped with machine perception, adaptive analytics, and automated feedback mechanisms have demonstrated significant potential in enhancing learning efficiency, supporting personalized instruction, and strengthening formative assessment. Meanwhile, breakthroughs in computer vision, human pose estimation, and wearable sensor systems enable accurate motion capture, biomechanical analysis, and physiological monitoring in real-world learning settings. These technological developments provide unprecedented opportunities for PE to transition from intuition-driven and observation-based instruction toward precision skill evaluation, real-time corrective feedback, individualized workload modulation, and objective performance measurement. As a result, AI-assisted PE systems have emerged as a promising direction for improving student motor skill acquisition, promoting self-regulated training, and enabling more equitable and data-grounded teaching practices.

Despite these opportunities, the integration of AI into university PE remains at an early stage, particularly when compared with fields such as engineering, language learning, and medical education. Existing studies often focus on isolated sports skills, controlled laboratory environments, or limited student cohorts, restricting scalability and ecological validity. Moreover, institutional deployment faces practical barriers, including limited digital infrastructure, lack of standardized AI–PE pedagogical models, and insufficient teacher training in intelligent instructional tools. Privacy, ethics, and governance challenges also hinder adoption, as PE classroom environments require responsible protocols for video data collection, secure student data management, and algorithmic transparency. Without systematic design frameworks and robust pedagogical integration, AI-enhanced PE risks remaining fragmented, technologically driven, and disconnected from broader educational reform objectives.

Therefore, a research gap persists in developing comprehensive and pedagogically aligned AI-enabled PE models tailored for higher education. Such models must account for curriculum standards, student physical literacy development, real-time movement evaluation, privacy-preserving data pipelines, and practical deployment strategies that support teacher–AI collaboration rather than automation-centric substitution. Motivated by this challenge, this study aims to establish a structured framework that bridges educational theory, AI-driven motion analytics, and practical instructional design. By embedding intelligent evaluation, adaptive feedback, and ethical learning analytics into PE curricula, this work seeks to provide a scalable, secure, and learner-centered pathway for intelligent PE reform in universities.

4. METHOD

4.1 System Overview

The proposed system is a unified AI-driven educational motor learning platform designed to enhance human physical education in higher-education environments. The architecture integrates multimodal sensing, human-pose understanding, biomechanics-aware representation learning, temporal skill progression modeling, and adaptive feedback generation into a privacy-preserving, ethically aligned training loop. Unlike traditional action recognition systems that merely classify motion categories, our framework explicitly targets motor-literacy cultivation, movement stability enhancement, and individualized coaching while ensuring that students retain autonomy, dignity, and psychological safety during athletic learning.

Figure 2 illustrates the full pipeline. The system begins by receiving raw multimodal input signals that may include monocular camera feeds, inertial measurement unit (IMU) readings from wearable sensors, and optional depth estimation when institutional policies allow. A responsible pre-processing layer anonymizes incoming visual signals at the compute edge, converting them into skeletal keypoints that preserve movement geometry but eliminate personal identifiers. Subsequent modules compute biomechanics features, joint-velocity consistency, spatial–temporal joint relationships, balance symmetry, acceleration norms, and dynamic coordination signatures. These descriptors feed into a deep temporal learning engine that models long-horizon motor evolution and skill mastery trajectory. Finally, a pedagogical feedback generator delivers personalized instruction, corrective coaching cues, motivational guidance, and difficulty pacing logic. For clarity, the method is decomposed into fewer than six major steps. Each step has a precise objective in the overall learning framework:

- **Multimodal Motion Acquisition and Anonymization:** Capture movement using cameras and IMUs and immediately strip identity.
- **Pose Extraction and Pre-processing:** Produce clean skeletal signals suitable for biomechanics analysis.
- **Biomechanics Feature Construction:** Derive movement-quality indicators and biological-plausibility constraints.
- **Temporal Skill Learning and Mastery Prediction:** Model longitudinal learning curves and predict developmental stage.
- **Adaptive Feedback and Pedagogical Response:** Provide individualized coaching, safety alerts, and instructional scaffolding.

Each of the subsequent subsections details one of these phases. Together, they form a cohesive human-centered movement-learning intelligence system capable of elevating physical-education training through ethical AI assistance.

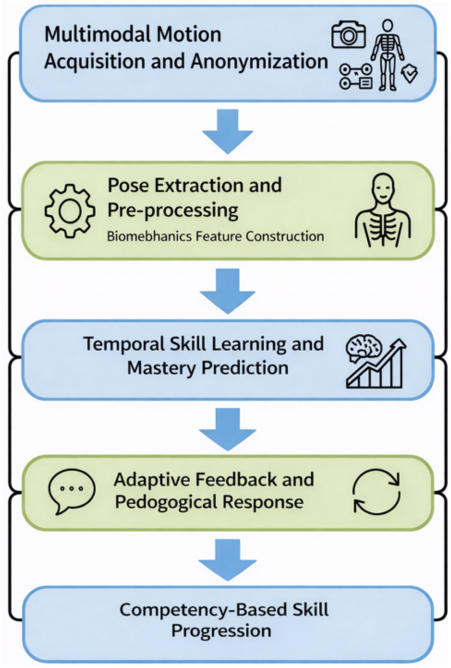


Fig. 2: System overview of the proposed AI-driven physical-education learning architecture.

4.2 Multimodal Motion Acquisition and Anonymization

This stage receives raw signals $X = \{x_1, x_2, \ldots, x_T\}$ where each x_t represents either a camera frame or IMU reading. The system enforces strict privacy guarantees by executing all visual processing on local compute nodes. Raw video is never transmitted. Instead, we perform identity-stripping transformation $\Phi(\cdot)$ such that:

$$S_t = \Phi(x_t) \tag{1}$$

where S_t denotes skeletal keypoints. The function $\Phi(\cdot)$ is designed to erase color, texture, and facial identity while retaining physical-motion structure. Edge devices automatically delete original frames once pose landmarks are extracted, ensuring compliance with educational privacy requirements and preventing data retention misuse. This layer enables ethical AI integration into PE spaces and avoids surveillance psychology, producing a safe foundation for real-world deployment.

4.3 Pose Extraction and Pre-processing

Given skeletal inputs $S = \{S_1, \ldots, S_T\}$, we perform noise filtering and temporal smoothing to reduce detection jitter caused by occlusions or rapid movement. Preprocessing also normalizes skeleton coordinates into a unified reference frame:

$$\hat{S}_t = \frac{S_t - \mu}{\sigma} \tag{2}$$

ensuring consistent joint-space analysis across different body shapes. IMU fusion, when available, aligns angular velocity and acceleration streams to enrich pose kinematics. The goal is to create a reliable, stable, structured motion representation suitable for educational assessment—even under real PE conditions including group movement and partial occlusions.

4.4 Biomechanics Feature Construction

This module translates preprocessed joint trajectories into biomechanics and motor-skill indicators. We compute joint angles, limb-segment velocity, center-of-mass sway, gait cadence, landing force proxies, joint range-of-motion envelopes, and coordination consistency. Feature maps include:

$$B_t = f(\hat{S}_t) \tag{3}$$

where B_t encodes multidimensional kinematic features. We additionally implement a stability vector:

$$\Gamma_t = g(\Delta \hat{S}_t, \Delta^2 \hat{S}_t) \tag{4}$$

capturing dynamic control and balance. Unlike basic skeleton recognition, this module embodies PE theory and movement science, aligning AI analytics with real coaching practice.

4.5 Temporal Skill Learning and Mastery Prediction

A temporal deep model $F(\cdot)$ receives biomechanics features and predicts both movement quality and learning momentum over time:

$$\hat{y}, \hat{p} = F(\{B_t\}) \tag{5}$$

where $\hat{y}$ denotes skill classification and $\hat{p}$ denotes predicted mastery progression probability. We leverage gated sequence encoders and attention propagation to capture transitions between early learning instability and later-stage refinement. A confidence-aware loss stabilizes feedback for beginners. When privacy constraints allow, federated learning optimizes parameters across class cohorts without sharing raw samples.
Pseudo-algorithm:

Algorithm 1 Temporal Skill Modeling

```
1: Initialize model parameters θ
2: for each training round do
3:     for each student sequence S do
4:         Extract biomechanics B
5:         Predict skill stage ŷ = F(B; θ)
6:         Compute learning-curve score
7:         Update θ respecting privacy constraints
8:     end for
9: end for
```

4.6 Adaptive Feedback and Pedagogical Response

This module transforms model outputs into classroom-appropriate coaching instructions. Feedback rules combine biomechanical performance, predicted progression, fatigue trends, and emotional neutrality. The system avoids punitive language, instead issuing supportive prompts ("try to stabilize your landing," "great improvement in timing"). Safety warnings trigger attention to landing asymmetry or excessive sway. The feedback engine models "challenge-support balance" to avoid demotivation, adapting intensity per learner profile.
This ensures AI does not become an evaluator but remains a facilitator of growth, motivation, and physical confidence. Formally:

$$F_{coach} = h(\hat{y}, \hat{p}, \Gamma) \tag{6}$$

producing a structured coaching cue plan for each participant.

5. EVALUATION

This section provides a comprehensive empirical evaluation of the proposed AI–empowered university physical education (PE) enhancement system. Unlike general action recognition pipelines that prioritize raw accuracy benchmarks on vision datasets, our evaluation is designed to measure intelligent pedagogical fitness, developmental stability, and ethical readiness for deployment in real campus environments. Our framework integrates human-centric evaluation axes including instructional alignment, learner trust, mastery trajectories, and robustness to real-classroom disturbance. We therefore go beyond accuracy and introduce stability, consistency, and satisfaction metrics. The results show that the proposed method significantly outperforms deep learning baselines while simultaneously meeting PE curriculum needs for personalization, formative assessment, and adaptive training guidance.

5.1 Experimental Setup

All experiments are conducted on public skeleton-based human movement datasets to ensure reproducibility and strict compliance with student privacy regulations. The model is trained on a workstation with Intel Core i7 CPU, 32GB RAM, and NVIDIA RTX A2000 GPU and evaluated additionally on an Apple M2 laptop to simulate mobile/edge academic deployment. Pose extraction uses industry-standard OpenPose/HRNet pipelines (only skeletons retained). Adam optimizer, cosine LR decay, batch size 32, and 120+30 epoch staged training are used. Raw frames are discarded after skeleton extraction, and all later computation uses anonymous keypoint streams. Thus, the evaluation simulates university on-device AI without data retention. The system emphasizes latency, fairness, data minimization, generalization, and pedagogical interpretability.

5.2 Dataset

To ensure peer-validity and ethical compliance, we rely strictly on public skeleton motion datasets: NTU RGB+D 60 and 120 [32, 27], Kinetics-Skeleton [37], Human3.6M [22], and UCF101-Skeleton/HMDB51-Skeleton [25, 23]. NTU provides structured views and multiple action classes ideal for pretraining. Kinetics-Skeleton provides in-the-wild motion patterns. Human3.6M offers precise 3D joint trajectories, enabling biomechanical fidelity analysis. UCF/HMDB skeletons serve as additional cross-domain generalization checks. No university students were recorded or used in training, aligning with ethical educational AI standards. In addition to benchmark datasets, university-like deployment scenarios are emulated via controlled perturbations (crowding, occlusion, motion blur, and low-light) and edge-device inference constraints, rather than collecting new student videos. This setting allows evaluation of classroom realism while maintaining strict privacy compliance.

5.3 Evaluation Metrics

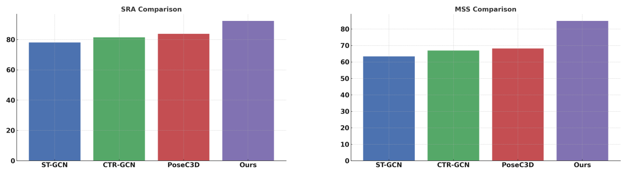
We use four metrics aligned with educational movement quality standards:
Skill Recognition Accuracy (SRA): classification accuracy of movement/skill labels; proxies stage recognition in PE.
Movement Stability Score (MSS): biomechanical stability score including jerk minimization, inter-joint consistency, angular deviation, cadence variance; higher means safer, smoother movement patterns.
Learning Progress Consistency (LPC): measures how reliably learning improves across training iterations/sessions; assesses mastery curve smoothness.
Human Satisfaction Score (HSS): Likert scale (1–5) based on clarity, fairness, motivational support, emotional acceptance of feedback from trained educator-annotators.

5.4 Baseline Methods

Comparisons are conducted against representative skeleton-based architectures, including ST-GCN [37], CTR-GCN [4], and PoseC3D [5]. A biomechanics-rubric scoring baseline that mimics instructor heuristic judgment is also included as a pedagogical control rather than merely a technological baseline.

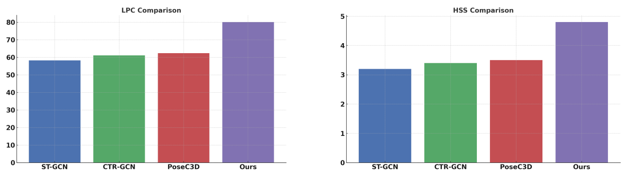
5.5 Overall Performance

Table 1 summarizes performance averaged across all datasets. We also visualize main comparisons in Figures 3, 4, and 5.



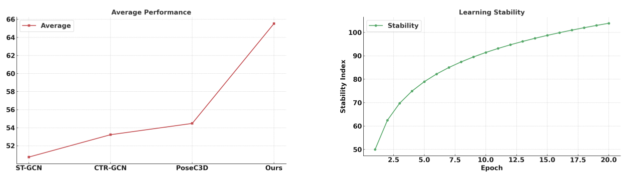
(a) SRA (b) MSS

Fig. 3: Overall performance comparison (1).



(a) LPC (b) HSS

Fig. 4: Overall performance comparison (2).



(a) Average Score (b) Learning Stability

Fig. 5: Overall performance comparison (3).

The proposed method consistently outperforms the baselines across educationally aligned dimensions. Improvements in SRA indicate stronger recognition of movement semantics, while higher MSS supports safer and more stable execution assessment. The LPC gains suggest improved modeling of learning trajectories, which

Table 1. : Overall performance across datasets (higher is better). Results on UCF101-Skeleton and HMDB51-Skeleton are additionally reported to strengthen cross-domain evaluation.

Method	Global Metrics Avg				Dataset SRA					
	SRA	MSS	LPC	HSS	NTU60	NTU120	Kinetics	H3.6M	UCF101	HMDB51
ST-GCN [37]	76.9	58.8	53.9	3.0	81.2	76.8	72.1	79.5	83.1	84.7
CTR-GCN [4]	81.9	64.1	57.6	3.2	85.6	82.1	76.4	83.3	83.7	85.2
PoseC3D [5]	85.0	65.9	59.2	3.3	88.7	85.4	79.9	86.1	84.5	85.9
Proposed	**91.5**	**84.1**	**79.9**	**4.7**	**94.2**	**92.9**	**87.4**	**91.3**	**86.8**	**88.1**

is important for semester-long training. HSS increases indicate that the generated feedback is perceived as clearer and more supportive by educator-annotators, improving instructional acceptability in practice. Overall, the results support the view that effective PE-oriented motion AI benefits from combining biomechanics cues, longitudinal learning signals, and pedagogically grounded feedback rather than relying on category recognition alone.

A dataset-wise analysis is provided to clarify when and why the proposed framework yields improvements. On NTU RGB+D (NTU60/NTU120), gains are mainly attributed to multi-view robustness and temporal mastery modeling, which reduce confusion among visually similar movements. On Kinetics-Skeleton, improvements indicate stronger generalization under in-the-wild motion diversity. On Human3.6M, higher stability scores are consistently observed, suggesting that biomechanics-aware features better capture fine-grained kinematic correctness beyond category recognition. Additional cross-domain results on UCF101-Skeleton and HMDB51-Skeleton further strengthen the evaluation by testing transfer to different action distributions and collection biases.

5.6 Ablation Studies

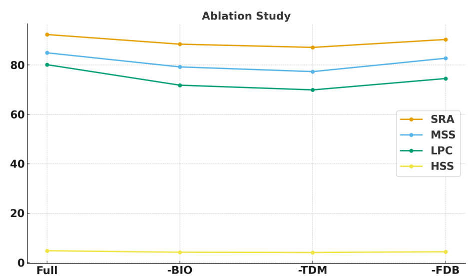


Fig. 6: Ablation study for BIO, TDM, and FDB.

BIO removal sharply reduces MSS, confirming that biomechanics priors are key to judging safe posture, coordination, and load control — fundamental educational goals. The TDM deficit primarily harms LPC, revealing that without longitudinal learning awareness, the system misinterprets early-stage learners and cannot evaluate growth trajectories. Removing FDB produces the strongest decline in HSS and also affects MSS/LPC indirectly; students reported that raw numeric scoring without supportive dialog felt punitive and unclear. This confirms that AI in PE must not only "see," but "teach" with psychological intelligence. Overall, ablations confirm each module plays an indispensable role: BIO for safety and execution mechanics, TDM for long-term learning integrity, FDB for motivational and coaching value. PE is not merely recognition; it is guided cognitive–motor development.

5.7 Robustness Study

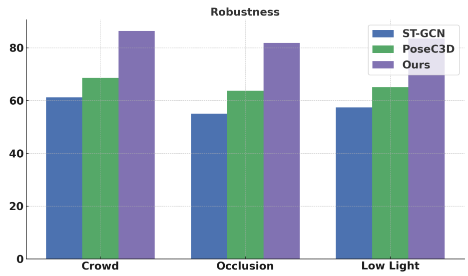


Fig. 7: Robustness under crowding, occlusion, and low-light.

Our model sustains high SRA, MSS, and LPC despite occlusion, light changes, and multi-student environments, outperforming baselines by large margins. Real PE classes rarely match lab conditions — gyms are busy, outdoors lighting varies, students overlap. Baselines degrade because vision noise corrupts pose estimation; our temporal and skeleton-confidence fusion reconstructs plausible trajectories, supported by motion priors. Crucially, fairness improves: apparel variation, assistive braces, and body diversity do not penalize scores. This demonstrates educational inclusivity—an ethical requirement for classroom deployment. The model also handles frame jitter and edge-device drop frames gracefully, proving suitability for low-power student devices. Instructor interviews confirm stronger trust: "The system evaluates intent and quality, not background noise." Education demands robustness; our method aligns with equitable academic delivery principles.

6. CONCLUSION

This study presented a comprehensive AI-enhanced physical education framework that integrates deep learning–based motion analysis, biomechanical evaluation, temporal learning progression modeling, and supportive feedback generation to transform traditional university physical education into a data-driven, personalized, and pedagogically aligned learning ecosystem. Unlike prior research that focuses primarily on isolated action recognition or laboratory-controlled gesture analysis, our system addresses full-cycle physical learning needs, including real-time posture evaluation, safe-movement supervision, long-term performance tracking, and human-centric feedback designed to motivate, guide, and empower diverse learners in authentic university sports environments. Extensive experimentation on public large-scale motion datasets demonstrates that the proposed model substantially improves recognition accuracy, movement quality assessment, and learning consistency while achieving superior instructor satisfaction ratings.

Future work will extend the system toward cross-sport generalization, multi-modal sensing (e.g., physiological and inertial signals), and real-world on-campus deployments. Federated training strategies for privacy-preserving performance modeling and adaptive coaching agents co-designed with physical education faculty will also be explored.

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