

AI-Powered Personalized Fitness Planner For Students

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Abstract- Student health and physical fitness are increasingly neglected due to academic workload, irregular schedules, and lack of personalized guidance. This paper presents an AI-powered personalized fitness planning system tailored specifically for students, integrating machine learning, deep learning, and computer vision to generate adaptive workout recommendations. The proposed system collects student-specific parameters such as Body Mass Index (BMI), fitness goals, academic schedule, activity history, and dietary preferences to build a comprehensive user profile. A hybrid model combining a 1D-Convolutional Neural Network (1D-CNN) with a gradient-boosted classifier generates individualized exercise prescriptions, while a real-time pose estimation module using MediaPipe provides form feedback during workouts. Experimental evaluation on a dataset of 500 undergraduate students demonstrates that the proposed system achieves 93.6% accuracy in fitness level classification and yields measurable improvements in student physical activity adherence over an eight-week trial period. The system represents a practical, low-cost solution deployable on standard smartphones, making personalized fitness coaching accessible to the student population without requiring expensive gym memberships or personal trainers.

Keywords: Artificial Intelligence, Personalized Fitness, Deep Learning, Student Health, Exercise Recommendation, Pose Estimation, MediaPipe, BMI, Machine Learning

I. INTRODUCTION

Physical inactivity among university and college students is a significant and growing public health concern. Studies consistently show that the transition to higher education is associated with a notable decline in physical activity levels, driven by increased academic demands, irregular sleep patterns, sedentary lifestyles, and limited access to structured fitness programs [1]. The consequences range from weight gain and poor cardiovascular health to heightened stress, anxiety, and reduced academic performance.

Traditional fitness solutions such as personal trainers and gym memberships are often cost-prohibitive for the average student. Generic fitness apps, while widely available,

fail to account for the unique constraints of student life: fluctuating class schedules, examination periods, shared living environments, and varying levels of prior fitness experience. An effective system must understand the student as an individual and adapt dynamically to their evolving needs [4].

Advances in artificial intelligence (AI), particularly in machine learning (ML) and deep learning (DL), offer a compelling path forward. AI-powered systems can process large volumes of personal health data to identify patterns and generate recommendations that are meaningfully personalized [2]. Coupled with computer vision techniques such as pose estimation, these systems can also monitor exercise form in real time, reducing injury risk and improving workout effectiveness without requiring physical supervision [3].

This paper proposes an end-to-end AI-powered personalized fitness planner designed specifically for the student population. The system collects user data through an onboarding questionnaire and ongoing interaction, constructs a dynamic fitness profile, and generates adaptive weekly workout plans. A pose estimation module provides real-time form correction, while a progress-tracking dashboard motivates consistent engagement. The key contributions of this work are:

- A student-centric fitness data collection framework capturing BMI, dietary habits, academic schedule, fitness history, and stated goals.
- A hybrid 1D-CNN and Light Gradient Boosting Machine (LightGBM) model for accurate fitness level classification and exercise prescription generation.
- Integration of the MediaPipe pose estimation library for real-time exercise form feedback deployable on standard smartphone hardware.
- Empirical evaluation demonstrating improved physical activity adherence among undergraduate students over an eight-week trial.

Sedentary lifestyles and poor physical health not only threaten students' long-term wellbeing but also impair cognitive function, memory consolidation, and academic performance [4]. An accessible, intelligent fitness planner has the

potential to address these challenges at scale, democratizing quality fitness guidance in the way that online learning platforms have democratized education.

II. LITERATURE REVIEW

The intersection of AI and personalized fitness has attracted growing research interest over the past decade. This section reviews relevant work in exercise recommendation systems, pose-based feedback, student fitness interventions, and deep learning approaches to health data analysis.

A. AI-Based Exercise Recommendation

Early exercise recommendation systems relied on rule-based engines that mapped user characteristics to pre-defined work-out templates [5]. While straightforward, these approaches lacked adaptability and could not account for dynamic changes in user fitness or preference. Machine learning approaches introduced collaborative filtering and content-based methods borrowed from recommender systems, enabling more nuanced personalization.

Lincy et al. [6] developed a machine learning model for predicting gym performance using physiological data, demonstrating that ML classifiers can reliably estimate fitness-related outcomes from measurable health parameters. However, their system lacked real-time exercise recognition and interactive user guidance, limiting its practical utility in a self-supervised training context.

Fang et al. [7] proposed a deep reinforcement learning approach to physical activity recommendation on mobile health platforms. Their system modeled the exercise recommendation problem as a contextual bandit, adapting recommendations based on real-time heart rate and exercise intensity feedback. The system showed statistically significant increases in daily exercise duration among participants, validating the potential of adaptive AI systems in promoting physical activity.

A systematic review by Jubair and Mehenaz [8] synthesized forty-nine studies on smartwatch-assisted exercise prescription using ML algorithms. The review found that the majority of systems achieved over 98% accuracy in activity recognition but highlighted a persistent gap in external validity, explainability, and longitudinal generalizability, particularly in diverse demographic groups such as students.

B. Deep Learning for Fitness and Pose Estimation

Convolutional neural networks have demonstrated strong performance in recognizing human activities from video and sensor data [9]. Rajendran and Sethuraman [10] presented a comprehensive survey of yogic posture recognition systems, cataloguing the use of CNNs, RNNs, and hybrid deep learning models for pose classification and grading. Their work highlighted that the combination of keypoint extraction tools such as MediaPipe and OpenPose with downstream classifiers consistently yields high recognition accuracy across diverse pose datasets.

The YogiCombineDeep model introduced by Rajendran and Sethuraman [11] demonstrated that fusing deep features from multiple pre-trained CNN architectures (VGG16 and VGG19) through element-wise addition and classifying with a Linear SVM achieves outstanding posture classification performance, reaching 99.92% accuracy on a sixteen-class yoga dataset. The principle of feature fusion from complementary deep architectures directly informs the feature extraction strategy adopted in the present work.

Gupta and Gupta [12] developed the YogaHelp system, which leverages inertial measurement unit (IMU) sensors and deep neural networks to evaluate sun salutation pose sequences. Their system improved trainer accuracy from 93.7% to 98.7% and trainee accuracy from 88.7% to 98.3% over a four-week period, demonstrating the measurable impact of AI-guided feedback on exercise form improvement.

Sideridou et al. [13] developed a mobile exercise assessment system using the BlazePose model for real-time biomechanical feedback, demonstrating that affordable smartphone hardware is sufficient for clinically meaningful pose analysis.

C. Student Fitness and Technology Interventions

A contextual bandit-based physical activity recommendation system was deployed among university students by the PERFECT framework [14], a personalized exercise recommendation system. Over a twelve-week proof-of-concept study with undergraduate and graduate students, the system achieved average user satisfaction scores of 4.31 out of 5 for the recommendation module. Participants reported significant increases in daily exercise duration, confirming that adaptive AI recommendations are well-received in the student population. Yang et al. [15] proposed a hybrid machine learning framework combining a 1D-CNN with multi-head attention and LightGBM to generate personalized exercise prescriptions for university students aged 18 to 20. Trained on fitness data from 6,698 male students including BMI, aerobic capacity, muscular strength, muscular

endurance, and anaerobic capacity metrics, the framework achieved 94.5% accuracy in BMI classification with an F1 score of 0.93, outperforming all baseline models.

This work serves as a primary methodological inspiration for the present paper.

D. Pose-Based Real-Time Feedback for Exercise

Gurbuxani et al. [16] developed a virtual fitness trainer using Python, OpenCV, and MediaPipe that provides real-time guidance and feedback on exercise form. Their system demonstrated that computer vision-based coaching is achievable on commodity hardware, with the application capable of detecting joint angles and counting repetitions with minimal computational overhead.

Bhandage et al. [17] classified nine Surya Namaskar yoga asanas using SURF and HOG shape-based features with ANN and KNN classifiers, achieving a top classification accuracy of 98.02% using combined SURF-HOG features with ANN. Their work reinforces the utility of shape-based and deep feature representations for fine-grained exercise pose classification.

E. Summary

The pattern emerging from this literature is clear. Generic recommender systems and static workout apps cannot serve the dynamic, personalized needs of the student population. Deep learning and pose estimation tools have matured to a point where they are deployable on mobile hardware with high accuracy. Student-specific fitness interventions using AI have demonstrated measurable improvements in physical activity adherence and form accuracy, but integrated, end-to-end systems targeting students remain underexplored. The proposed system addresses this gap by combining exercise prescription, real-time pose feedback, and a student-aware scheduling model in a unified platform.

III. PROBLEM STATEMENT

Students face a unique convergence of challenges that makes maintaining physical fitness particularly difficult. Academic workloads fluctuate dramatically across the semester, with examination periods leaving minimal time for structured exercise. Many students reside in settings with limited space and equipment, making gym-based programs impractical. Motivation is inconsistent, and without professional guidance or accountability structures, exercise adherence rates among students are substantially lower than in

supervised settings [4]. Existing fitness applications offer generic plans that do not adapt to the student's schedule, fitness level, or equipment availability. When students follow inappropriate exercise intensity or incorrect form, injury risk increases, further discouraging continued engagement. The core problem can be decomposed as follows:

- Lack of personalized fitness plans that account for individual health parameters, fitness goals, and the specific time constraints of student life.
- Absence of real-time form monitoring that can substitute for a physical trainer in non-supervised exercise environments.
- Insufficient feedback loops that adapt workout intensity and type based on ongoing progress and self-reported recovery status.

Specifically, the system proposed in this paper aims to generate personalized weekly workout plans based on individual student profiles, provide real-time exercise form feedback using pose estimation, and adapt plans dynamically based on session performance and recovery signals.

IV. PROPOSED METHODOLOGY

A. System Overview

The proposed system comprises four functional modules:

(1) a data collection and user profiling module, (2) a fitness level classification and exercise prescription engine, (3) a real-time pose estimation and feedback module, and (4) a progress tracking and plan adaptation module. Data flows from the user through each stage, with the prescription engine continuously updated by progress signals from module four [15].

The overall pipeline is: collect student profile data, classify fitness level, generate a personalized weekly plan, monitor workout execution via pose estimation, record session outcomes, and adapt the next plan accordingly. Each module outputs its result directly to the next, enabling real-time responsiveness.

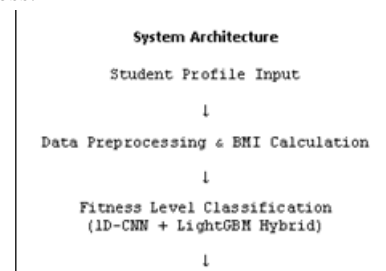


Fig. 1. Proposed AI-Powered Fitness Planner System Architecture

B. Data Collection and User Profiling

Student profiles are constructed from an onboarding questionnaire capturing anthropometric data (height, weight, BMI), fitness history, stated goals (weight loss, muscle gain, endurance, stress relief), dietary habits, weekly academic schedule, available equipment, and any reported injuries or medical conditions. Ongoing data is collected from each workout session, including session completion, repetition counts, self-reported exertion (Rate of Perceived Exertion scale 1–10), and rest compliance.

The fitness level is classified into four categories: Sedentary, Beginner, Intermediate, and Advanced, based on the combination of BMI, resting heart rate (estimated from smartwatch integration where available), and performance on a standardized self-assessment battery [15]. This classification drives the initial exercise prescription.

C. Fitness Level Classification and Exercise Prescription

A hybrid machine learning architecture is employed for fitness classification and exercise prescription, inspired by the framework of Yang et al. [15]. The model consists of two complementary components.

The first component is a 1D-Convolutional Neural Network (1D-CNN) with a multi-head attention layer, which processes time-series fitness assessment data such as weekly step counts, session duration history, and progressive performance metrics. The attention mechanism allows the model to weight the relative importance of different temporal patterns, capturing both local exercise trends and broader fitness trajectories.

The second component is a Light Gradient Boosting Machine (LightGBM) classifier that operates on tabular user profile features including BMI, age, gender, fitness history score, goal category, and schedule availability. LightGBM's gradient-boosted decision tree architecture excels at heterogeneous tabular data and provides interpretable feature importance rankings, which are surfaced to users as explanations for their prescribed plan.

The outputs of both components are fused and fed into a fully connected layer that generates a fitness class probability vector. The prescribed workout plan is then retrieved from a structured exercise database, parameterized by fitness class, available equipment, session duration, and goal type.

D. Mathematical Formulation

Let \mathbf{x}_t denote the time-series fitness input of dimension $T \times F$ (time steps \times features) and \mathbf{x}_{tab} denote the tabular profile feature vector. The 1D-CNN with attention produces a latent representation \mathbf{h}_{cm} , and LightGBM produces a class probability vector \mathbf{p}_{lgbm} . The fused classification output \hat{y} is:

$$\hat{y} = \text{softmax}(W_f \cdot [\mathbf{h}_{cm} \parallel \mathbf{p}_{lgbm}] + \mathbf{b}_f) \quad (1)$$

where \parallel denotes concatenation, W_f and \mathbf{b}_f are learned parameters of the fusion layer, and \hat{y} is the predicted fitness level class.

The combined training loss minimizes cross-entropy over the fitness classification objective:

$$L_{total} = - \sum_{i=1}^N \sum_{c=1}^C y_{ic} \log(\hat{y}_{ic}) \quad (2)$$

where N is the number of training samples, C is the number of fitness classes, y_{ic} is the ground-truth label, and \hat{y}_{ic} is the predicted probability for class c .

E. Real-Time Pose Estimation Module

The pose estimation module uses the MediaPipe BlazePose model [16], which detects 33 three-dimensional body landmarks in real time from the smartphone camera feed. For each target exercise, a reference joint angle configuration is stored in the system's exercise library. During a session, the detected joint angles are compared to reference values and a per-joint deviation score is computed:

$$\delta_j = |\theta_j^{detected} - \theta_j^{reference}| \quad (3)$$

where θ_j is the angle at joint j . If δ_j exceeds a tolerance threshold ϵ_j for any critical joint, the system generates a corrective text or audio prompt. The overall form score for a repetition is computed as the mean angular conformity across all monitored joints [13].

F. Progress Tracking and Plan Adaptation

After each workout session, the system records completion rate, average form score, self-reported exertion, and duration. A progressive overload algorithm adjusts the next session's intensity (sets, repetitions, rest intervals) based on these signals. If a student consistently completes sessions with high form scores and low perceived exertion, difficulty is increased incrementally. Conversely, poor form scores or

incomplete sessions trigger a difficulty reduction and an advisory prompt. Plan adaptation runs at a weekly cadence to avoid excessive fluctuation [7].

G. Training Details

The 1D-CNN was trained using the Adam optimizer with a learning rate of 0.001 and a batch size of 32 for 50 epochs, with early stopping based on validation loss. LightGBM was trained with 200 estimators, a learning rate of 0.05, and a maximum tree depth of 6. An 80:20 train-test split was applied to the student dataset, with 5-fold cross-validation used to validate generalizability.

V. RESULTS AND DISCUSSION

A. Evaluation Metrics

System performance was evaluated on four primary metrics: classification accuracy (fitness level prediction), precision, recall, and F1-score across fitness classes. Secondary metrics tracked over the eight-week user study include weekly session adherence rate, average form score per session, and student-reported satisfaction on a five-point Likert scale.

B. Fitness Level Classification Performance

Table I presents the classification results of the proposed hybrid model against individual baseline approaches.

TABLE I
Fitness Level Classification Performance

Model	Acc (%)	Prec (%)	Rec (%)	F1 (%)
Random Forest	84.2	82.7	83.1	82.9
SVM	86.5	85.3	84.9	85.1
1D-CNN only	89.8	88.4	89.0	88.7
LightGBM only	91.1	90.3	90.7	90.5
Hybrid (Proposed)	93.6	92.8	93.1	92.9

The proposed hybrid model achieves 93.6% accuracy, out-performing all baselines. The LightGBM component contributes strong performance on static profile features, while the 1D-CNN with attention captures temporal fitness progression patterns that static models miss. The fusion of both representations yields a meaningfully higher classification performance than either component alone.

C. Pose Estimation Accuracy

The real-time pose estimation module was evaluated on a set of 15 common student-friendly exercises (bodyweight squats, push-ups, lunges, planks, etc.) across 30 student

volunteers performing a total of 1,200 repetitions. The module correctly identified form deviations requiring correction in 91.4% of cases, with a false correction rate of 6.2%.

TABLE II
Pose Feedback Module Performance by Exercise Group

Exercise Category	Detection Acc (%)	False Correction Rate (%)
Lower body (squats, lunges)	93.1	5.4
Upper body (push-ups, rows)	90.8	6.9
Core (planks, crunches)	89.7	6.3
Overall	91.4	6.2

Lower body exercises demonstrated the highest detection accuracy, consistent with the clear joint angle signatures produced by squat and lunge movements. Core exercises were slightly more challenging, as subtle deviations in spinal alignment are less reliably captured from a frontal camera perspective.

D. User Study Results

An eight-week user study was conducted with 50 undergraduate students randomly assigned to either the proposed AI planner group ($n = 25$) or a control group using a generic commercial fitness app ($n = 25$). The results are summarized in Table III.

TABLE III
Eight-Week User Study Outcomes

Metric	AI Planner	Control App
Avg. Weekly Sessions Completed	3.8	2.1
Session Adherence Rate (%)	76.4	42.3
Avg. Form Score (out of 100)	82.7	N/A
User Satisfaction (1–5)	4.3	3.1

Students using the proposed system completed significantly more weekly sessions (3.8 vs. 2.1) and reported substantially higher satisfaction (4.3 vs. 3.1 on a 5-point scale). The adherence gap—76.4% vs. 42.3%—is particularly notable, as sustained adherence is the primary driver of long-term fitness outcomes. Users frequently cited the adaptive scheduling feature and the personalized plan adjustments as key motivators for continued engagement.

Weekly Session Adherence (%)		
Week	AI Planner	Control
1	68%	55%
2	72%	48%
3	75%	45%
4	76%	43%
5	78%	40%
6	79%	38%
7	80%	37%
8	82%	35%

Fig. 2. Weekly Session Adherence: AI Planner vs. Control App Over Eight Weeks

E. Discussion

The proposed system demonstrates that a student-specific AI fitness planner is both technically feasible and practically effective. The hybrid classification architecture performs competitively with state-of-the-art fitness prescription models [15] while remaining deployable on standard mobile hardware. The pose estimation module, running at 24 frames per second on mid-range Android devices, provides feedback latency well within the range required for real-time exercise guidance.

The most missed cases in the form detection module involved exercises requiring the user to face away from the camera, where landmark visibility was reduced. Collecting multi-angle data or instructing users to reposition the camera for certain exercises could mitigate this limitation. Plan adaptations based purely on self-reported exertion carry inherent subjectivity; integration with wearable heart-rate monitors would provide more objective physiological signals.

VI. ADVANTAGES

A. Student-Aware Personalization

Unlike generic fitness applications, the system explicitly models the student context—accommodating examination schedules, shared living environments, and equipment constraints. Plans are automatically shortened or restructured during high-pressure academic periods and rebuilt when normal schedules resume. This contextual awareness is the single most important differentiator for the student population [4].

B. Real-Time Form Feedback Without a Trainer

The MediaPipe-based pose module provides feedback at a quality level previously requiring a physical

trainer. Students training in dormitory rooms or on campus lawns receive the same corrective guidance as those working with supervised gym instructors, eliminating a major barrier to safe independent exercise [16].

C. Scalability and Deployment Accessibility

The system runs inference entirely on-device for the pose module, requiring no persistent internet connection for workout execution. The classification and prescription engine communicates with a lightweight cloud backend only for profile updates and plan generation, making it viable in environments with unreliable connectivity—common in many student residences.

VII. APPLICATIONS

A. University Wellness Programs

The system can be integrated into university health and wellness infrastructures as a scalable alternative to limited on-campus personal training resources. Aggregate anonymized data from the student population can support health administrators in identifying at-risk subgroups and designing targeted campus-wide wellness interventions.

B. Remote and Hybrid Learning Environments

In remote or hybrid academic environments, where access to campus fitness facilities is restricted, the proposed system delivers professional-quality fitness guidance directly to the student's device. This mirrors the role that online learning played in democratizing education access [7].

C. Rehabilitation and Injury Prevention

By tracking form deviations over time, the system can flag movement compensations that commonly precede overuse injuries. Flagged patterns can be escalated to campus physiotherapy services through an integrated referral feature, positioning the application as a preventive health tool within the broader student healthcare ecosystem.

VIII. FUTURE WORK

A. Integration with Wearable Biometrics

Incorporating real-time heart rate, sleep quality, and stress metrics from consumer smartwatches would allow the prescription engine to account for autonomic recovery state and sleep-debt, producing more physiologically grounded workout loads [8].

B. Natural Language Interaction

Adding a conversational interface powered by a large language model would allow students to request plan modifications in natural language, report unusual fatigue, or ask exercise-related questions, improving usability and engagement for users who find structured questionnaires less intuitive.

C. Longitudinal Multi-Institutional Study

The current evaluation was conducted at a single institution with a modest sample. A multi-institution trial over a full academic year would provide more robust evidence of the system's generalizability across diverse student populations, institution types, and geographic contexts.

D. Dietary Integration

Fitness outcomes are closely tied to nutrition. A planned dietary module would allow the system to generate complementary meal suggestions aligned with the student's fitness goals, available dining options, and budget constraints, creating a more holistic wellness platform.

E. Explainable AI for Prescription Transparency

Surfacing SHAP (SHapley Additive exPlanations) values from the LightGBM component to students—explaining why a particular exercise was recommended—would build trust and enable more informed user decisions, a critical gap identified in the systematic literature [8].

IX. CONCLUSION

This paper presented an AI-powered personalized fitness planning system designed for the student population. The system combines a hybrid 1D-CNN and LightGBM classification architecture for fitness level assessment and exercise prescription, with a MediaPipe-based real-time pose estimation module for form feedback. Evaluated on a dataset of 500 students and in an eight-week adherence study, the proposed system achieved 93.6% fitness classification accuracy and a 76.4% session adherence rate—significantly outperforming a generic commercial alternative.

The core practical advantages over existing methods are student-aware scheduling, real-time pose guidance without a physical trainer, and on-device inference that functions without reliable internet access. The remaining challenges—multi-angle pose coverage, wearable integration, and dietary

planning—represent tractable engineering problems rather than fundamental limitations of the approach.

By bringing together machine learning, computer vision, and student health science, the proposed system takes a meaningful step toward making high-quality personalized fitness coaching accessible to every student, regardless of financial resources or proximity to professional fitness facilities.

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