

FITSHIELD: PERSONALIZED FITNESS AND NUTRITION RECOMMENDATION MOBILE APPLICATION

AI-BASED EXERCISE POSTURE RECOGNITION AND INJURY PREVENTION SYSTEM

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Project Proposal Report

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DECLARATION

I declare that this is my own work, and this proposal does not knowingly incorporate any material previously submitted for a degree or diploma at any other university or higher education institution, nor does it contain any material that has been previously published or written by another person apart from where proper acknowledgment is given in the text.

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ABSTRACT

Maintaining an effective fitness standard while reducing any injuries caused is considered an accurate exercise execution. When we analyze the present-day fitness application, they mainly focus on a basic activity tracking systems and have a lack of real time posture analysis and feedback. The lack of these systems has reduced the workout effectiveness or even wouldn't live up to expectations that can be set. Therefore, there is a need for an intelligent system that can monitor user movements and provide immediate guidance.

In order to address this matter, this research proposes an AI based Posture Recognition Activity Tracking with a Motivational Feedback system. This system adapts computer vision to analyze the user's movements in real-time through a mobile camera. For pose estimation, trained models like MediaPipe / OpenPose are used that can detect body key points and calculate joint angles to ensure posture accuracy. This system can identify incorrect postures and give instant feedback for alignment changes.

As added features it also analyzes performance and measure workout durations. It provides a motivational feedback mechanism that encourages users with positive reinforcement when the exercises are done correctly.

This system aims to improve accuracy of the exercises, and evade risk of injuries. By integrating the real time posture analysis system and the motivational feedbacks would offer a more effective approach compared to the traditional fitness applications.

Keywords

Posture recognition, computer vision, pose estimation, activity tracking, real-time feedback

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LIST OF FIGURES & ABBREVIATIONS

AI - Artificial Intelligence

CV - Computer Vision

FPS - Frames Per Second

IQR - Interquartile Range

NFR - Non-Functional Requirement

PII - Personally Identifiable Information

ROI - Region of Interest

SLIIT - Sri Lanka Institute of Information Technology

SUS - System Usability Scale

SVM - Support Vector Machine

1. INTRODUCTION

1.1 Background and Context

With the growing popularity of mobile fitness applications, many individuals rely on digital platforms to perform exercises without expert supervision. Although these applications provide workout routines and basic tracking features, most lack the capability to accurately analyze user posture and deliver real-time corrective feedback [1], [2].

As a result, users frequently perform exercises incorrectly, which can negatively impact their health by causing joint pain, muscle tension, and long-term injuries. Proper posture plays a critical role in ensuring safe and effective workouts, especially under varying real-world conditions such as lighting, camera angles, and user differences, where current pose estimation systems still face challenges [3], [4].

Table 1.1: Existing Solutions and Limitations

Table 1.1 summarizes current computer vision fitness systems: Real-time pose estimation struggles with accuracy trade-offs; OpenPose requires high computational resources unsuitable for mobile; MediaPipe offers lightweight performance with minor occlusion trade-offs; GNN models have high complexity and lack explainability. Ideas for proposed solution: Record user movement via mobile camera, extract keypoints, compute joint angles, identify incorrect posture, and deliver encouraging motivational prompts.

1.2 Literature Review

Review of computer vision pose estimation across Huang et al. (2023), Lan et al. (2023), Wu et al. (2023), Chen et al. (2025), Ma et al. (2025), and Sun et al. (2025). Extracting spatial features from joint coordinates allows rapid kinematic analysis. Imbalance in human movement data requires robust data balancing strategies.

1.2 Literature Review (Cont.)

Lightweight edge deployment is essential for mobile adoption. Transformer models are too heavy for edge phones. Graph Neural Networks (GNNs) provide spatial modeling but require dedicated GPUs. Explainable feedback is critical so users understand simple corrective instructions like "Keep your back straight" or "Lower your hips".

Table 1.2.1: Literature Review Summary

Table 1.2.1 evaluates Huang et al. (2023), Lan et al. (2023), Wu et al. (2023), Chen et al. (2025), Ma et al. (2025), Sun et al. (2025), Zhiliang et al. (2025), Xia et al. (2025), and Kappan et al. (2026). Key limitations include sensitivity to occlusion, computational latency, and lack of real-time mobile adaptation.

1.3 Research Gap

Table 1.3.1 Justification: G1: Existing posture systems detect keypoints but lack explainable guidance; G2: Systems lack integration with repetition counting and progress tracking; G3: Real-time feedback struggles with mobile edge latency; G4: Systems do not identify recurring posture errors over time.

1.3 Research Gap (Cont.)

These four gaps justify the novelty of this component. The research is the first real-time, explainable, mobile-optimized pose recognition system integrating repetition counting and repeated error tracking.

2. OBJECTIVES

2.1 Main Objective

To develop an AI-powered, real-time posture recognition and intelligent fitness support system that accurately detects and evaluates exercise posture using mobile camera input, achieving classification accuracy $\geq 85\%$ and latency $< 1s$, with explainable corrective feedback and repetition counting.

2.2 Specific Objectives

SO1: Develop real-time posture detection achieving $\geq 85\%$ accuracy; SO2: Design explainable feedback with $\geq 80\%$ user satisfaction; SO3: Implement rep counting achieving $\geq 90\%$ accuracy.

2.2 Specific Objectives (Cont.)

SO4: Develop repeated mistake detection identifying $\geq 85\%$ of repeated errors; SO5: Optimize system for mobile edge maintaining response time ≤ 1 second during live exercise sessions.

3. METHODOLOGY

Design Science Research approach structured in four iterative phases: Phase 1: Data Collection & Preprocessing (MediaPipe keypoint extraction, IQR outlier filtering, normalization); Phase 2: Posture Detection Model (Random Forest and joint angle trigonometry); Phase 3: Real-Time Feedback and Repetition Counting; Phase 4: Mobile Integration.

3.2 Data Collection & Preprocessing

Three primary streams: (1) Real-time mobile video frames; (2) Public exercise datasets (squats, lunges, push-ups); (3) Custom recorded validation video under controlled conditions with SLIIT Research Ethics Committee approval.

3.3 Posture Detection & 3.4 Feedback

Feature engineering calculates joint angles (knee, hip, elbow, shoulder). State machine counts complete repetitions (e.g. descent -> bottom inflection -> ascent = 1 rep). Threshold rules detect alignment errors and generate audio/visual coaching.

3.5 Mobile Integration & 3.6 Pose Methods

Table 3.6.1 Pose Detection Methods: MediaPipe Pose selected for optimal balance of speed, accuracy, and mobile CPU compatibility over OpenPose and MoveNet.

Table 3.6.2 & 3.6.3 Methods Comparison

Table 3.6.2 Posture Evaluation: Rule-based joint angle analysis + Random Forest hybrid selected. Table 3.6.3 Activity Tracking: State Machine approach with threshold-based rep counting selected.

3.7 Tools and Platforms

Table 3.7.1 Tools: MediaPipe (Pose detection), OpenCV (frame preprocessing), Python / Scikit-learn (ML modeling), React Native / Flutter (mobile UI), MongoDB / SQLite (local workout history).

3.8 Ethical Considerations

Video streams processed in-memory on device; no raw video frames stored on external servers. Anonymized keypoint coordinates protect personal privacy. Voluntary participation with written informed consent.

3.9 Validation Strategy and Metrics

Model level: accuracy $\geq 85\%$, precision, recall, F1. System level: latency $< 1s$ at ≥ 15 FPS. User level: SUS usability testing with 15-20 participants targeting score ≥ 70 .

4. HIGH LEVEL SYSTEM ARCHITECTURE

FITSHIELD four-component system: Component 1 (AHEE Habit Engine), Component 2 (Exercise Posture Recognition & Repetition Counter), Component 3 (Smart Supplement Advisory), Component 4 (Dietary Safety & Interaction System).

Figure 1: System Component Diagram

Diagram illustrating video frame capture, MediaPipe inference, trigonometric angle calculation, state machine rep counting, and audio feedback dispatch.

4.3 Individual Component Architecture

Data Ingestion Layer (OpenCV frame extraction), Pose Detection Layer (MediaPipe landmarks), Activity Tracking Layer (State machine rep counter), Feedback Generation Layer (FastAPI / local sound synthesizer).

Figure 2: Component Architecture Flow

Detailed architectural flowchart illustrating input camera stream, joint angle calculation, posture threshold evaluation, and coaching output.

Table 4.3.1: Component Interactions

Table 4.3.1 outlines interaction between posture recognition outputs and the adaptive habit engine for routine adjustment.

4.5 Scalability and Security

Local edge processing eliminates heavy video upload bandwidth, ensuring instantaneous feedback, zero cloud streaming bottlenecks, and complete biometric privacy.

5. USER REQUIREMENTS

Table 5.1.1 Stakeholders: End fitness users, personal trainers, healthcare providers, and application developers.

Table 5.2.1 Functional Requirements FR-01 to FR-08 (camera capture, keypoints, angle calculation, correctness rules).

Table 5.2.1: Functional Requirements (Cont.)

FR-09 to FR-25: Multi-exercise support (squat, push-up, lunge), real-time correction messages, rep counting, repeated error detection, and workout duration logs.

Table 5.3.1: Non-Functional Requirements

NFR-01 (Latency $\leq 1s$), NFR-02 (≥ 15 FPS), NFR-03 (60 min continuous session), NFR-04 (Accuracy $\geq 85\%$), NFR-05 (Exercise recognition $\geq 80\%$), NFR-06 (Rep counting $\geq 90\%$), NFR-07 (99% uptime), NFR-08 to NFR-13 (Security & Usability).

Table 5.3.1: Non-Functional Requirements (Cont.)

NFR-14 (Visual indicators), NFR-15 (Concurrent support), NFR-16 (Scalability), NFR-17 (Modular maintainability), NFR-18 (Extensible exercise library).

6. COMMERCIALIZATION PLAN

Target Market: Fitness-conscious adults aged 18-40 exercising at home in Sri Lanka. Value Proposition: First real-time mobile posture coaching app delivering immediate injury prevention.

6.3 Cost Estimation & Revenue Model

Cost: Initial setup 10,000-15,000 LKR; Monthly 3,000-6,000 LKR. Pricing: Freemium model (basic posture free); Premium Individual (500-1,000 LKR/mo); Gym Trainer License (50,000-150,000 LKR/yr); B2B API access.

6.6 Intellectual Property Considerations

Original intellectual property in joint angle calculation matrices, state machine transition algorithms, and repeated mistake detection models protected by copyright and software patents.

7. BUDGET AND JUSTIFICATION

Table 7.1 Budget: Cloud Hosting (6,000 LKR), Software Tools (0 LKR - open source), Device Testing (4,000 LKR), User Participant Incentives (15,000 LKR), Dataset Preparation (8,000 LKR), Data Usage (8,000 LKR), Documentation (4,000 LKR). Total: 45,000 LKR.

8. WORK BREAKDOWN STRUCTURE (WBS)

Table 8.1 Work Packages: WP1 (Data Collection), WP2 (Pose Detection), WP3 (Posture Evaluation), WP4 (Activity Tracking & Mistake Detection), WP5 (Feedback System), WP6 (Testing & Evaluation).

Figure 3: Work Breakdown Chart

Hierarchical breakdown diagram for the two academic semesters.

9. GANTT CHART

Figure 4 Gantt Chart: Project milestones spanning data collection, algorithm tuning, mobile integration, and final viva voce presentation.

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