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AI-Powered Real-Time Fitness Tracking and Posture Detection System

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Abstract: Maintaining correct exercise form is essential for fitness effectiveness and injury prevention, yet most existing fitness applications focus solely on quantitative metrics such as step count, calories burned, and heart rate, ignoring qualitative aspects of movement correctness. This work introduces an AI-driven real-time fitness monitoring and posture analysis system that utilizes computer vision and deep learning techniques to evaluate exercise performance through a regular webcam without requiring wearable devices. The proposed framework uses MediaPipe Pose Estimation to identify 33 key body points in every video frame for real-time skeletal tracking. These pose features are processed by a CNN–LSTM hybrid model, where the Convolutional Neural Network (CNN) extracts spatialposture characteristics, while the Long Short-Term Memory (LSTM) module learns sequentialmovement patterns over time. The integrated pipeline automatically classifies exercises such as squats, push-ups, and lunges, counts repetitions accurately, and computes joint angles to identify postural deviations.Upon detecting incorrect form, the system delivers instant corrective feedback via visual alerts or voice prompts, mimicking the role of a personal trainer. Operating at over 30 FPS, the system ensures smooth real-time monitoring.Experimental evaluation demonstrates high exercise classification accuracy and effective posture correction, making professional-quality fitness coaching accessible and affordable to all users regardless of location or resources.
Keywords—Pose estimation, MediaPipe, CNN–LSTM, Exercise recognition, Repetition counting, Real-time posture correction, Human activity recognition, Computer vision, Deep learning.

I. INTRODUCTION

Fitness and physical well-being are increasingly prioritized globally,yetaccesstoprofessionalcoaching remainslimitedby cost, geography, and availability.Modern fitness applications have proliferated, but the majority rely on manual tracking or wearable sensors that capture only quantitative metrics such as time,distance,andcaloriesburned[1]. Thequalitativedimension of exercise—whether the movement is performed correctly—is largelyignored. Poorpostureduringworkoutsisaleadingcause ofmusculoskeletalinjuries,musclestrain,andlong-termphysical imbalance [7].

Recent developments in Artificial Intelligence, especially in the areas of computer vision and deep neural networks,makeit possible to analyze human motion in real time from standard video input. Pose estimation frameworks such as MediaPipe BlazePose [8] and OpenPose [4] can detect detailed body key points at low computational cost. Combined with sequence modelling architectures suchasCNN– LSTMhybrids[5],these toolsenableautomatedexerciserecognition,repetitioncounting, and posture analysis without specialized hardware.

ThispaperintroducesanAI-BasedReal-TimeFitness Tracker and Posture Detection System that: (i) captures live video viaa standard webcam;(ii) detects 33body landmarksper frame using MediaPipe; (iii) classifies exercises and counts repetitions using a CNN–LSTM model; (iv) computes joint angles to identify postural deviations; and (v)delivers immediate corrective feedback through visual or voice prompts. The system operates at over 30 FPS, bridging the gap between self-guided home workouts and professional coaching.

II. LITERATURE REVIEW

Research in human activity recognition (HAR) and vision- based fitnessmonitoring has advanced significantlyoverthepast decade.

Anguita et al. [1] presented one of the earliest HAR systems using smartphone accelerometer and gyroscope data. Their approach utilized machine learning algorithms such as Support Vector Machines along with neural network models— demonstrated that physical activities could be reliably classified frominertialsensorstreams, layingthefoundation for automated fitness monitoring.

Hammerla et al. [2] explored the use of Long Short-Term Memory(LSTM)networksforrecognizinghumanactivitiesfrom time-series sensor data, showing that LSTMs outperform traditional models in capturing temporal motion patterns essential for exercise recognition.

Zheng et al. [3] introduced CNN-based pose estimation for fitnessapplicationsincluding squatsand push-ups, demonstrating howconvolutionalnetworkscanextractspatialfeaturesfrombody postureimagesandevaluateexercisecorrectness,formingabasis for vision-based fitness monitoring systems.

Cao et al. [4] proposed **OpenPose**, a real-time multi-person 2D pose estimation framework using Part Affinity Fields.By efficiently extractingbody key pointsfrom RGBimages, Open- Posemadereal-timeexercisetrackingfeasiblewithoutspecialized hardware.

Ordonez and Roggen [5] introduced the **DeepConvLSTM** architecture, combining convolutional layers for spatial feature extractionwithLSTMlayersfortemporalmodelling.Thishybrid approach significantly improved HAR accuracy, directly influencing CNN–LSTM designs for exercise classification.

Alatiah and Chen [6] focused on real-time exercise recognition and repetition counting using pose estimation and machine learning, demonstrating accurate rep counting and exercise identification, paving the way for AI-based virtual fitness trainers.

Chenetal.[7]proposedanintelligentpersonaltrainersystem capable of detecting incorrect exercise posture and providing immediate corrective feedback, emphasizing injury prevention and workout effectiveness.

Sinclairetal.andGoogleResearch[8]demonstratedon-device, real-time pose tracking via **BlazePose**, operating directly on mobile hardware with low latency and without cloud dependency, supporting lightweight real-time AI fitness applications.

Existing systems either rely on wearable sensors, operate offline, or lack an integrated framework combining exercise recognition, repetition counting, and real-time posture correction. The proposed system addresses all these gaps in a single pipeline.

III. PROBLEM STATEMENT

Despite thewidespread availability offitness applications,no lightweight, wearable-free system currently integrates all of the following in a single real-time framework: automatic exercise recognition, accurate repetition counting, joint-angle-based posture analysis, and instant corrective feedback.Specifically, the key problems are:

1) Absence of posture analysis: Existing apps focus on quantitative metrics (calories, steps) but cannot evaluate form or movement quality.
2) Noreal-timecorrectivefeedback:Usersreceiveno immediate guidance when performing exercises incorrectly, increasing injury risk.
3) Wearable dependency: Many accurate systems require additional hardware (accelerometers, heart-rate monitors), increasing cost and reducing accessibility.
4) Limitedpersonalization:Rule-basedsystemscannotadapt to individual biomechanical variation or diverse exercise types.
5) Fragmented pipelines: Research systems typically address either pose estimation, exercise classification, or feedback, but not all three together.

IV. PROPOSED SYSTEM AND METHODOLOGY

A. *System Architecture*

The proposed system is a ten-step end-to-end pipeline from live video capture to real-time feedback delivery, illustrated in Fig. 1.

B. *Step-by-StepMethodology*

Step 1 – Video Capture: A standard webcam captures live video of theuser performing exercises. The system continuously receives video frames, ensuring adequate visibility of the user’s full body for accurate analysis.

↓

Step 2 – Frame Extraction:The captured video stream is divided into individual frames at a fixed rate. Each frame is processed independently while preserving temporal order, enabling continuous monitoring throughout the workout session.

↓

Step3–PoseEstimation:EachframeispassedtoMediaPipe PoseEstimation,whichdetects33keybodylandmarksincluding shoulders, elbows, hips, knees, and ankles, producing a skeletal overlay representation of the user’s body posture.

↓

Step 4 – Preprocessing: Extracted landmark coordinates are normalizedandcleanedtohandlevariationsinbodysize,camera distance,andorientation,improvingtherobustnessofdownstream deep learning models.

↓

Step5 – CNN Feature Extraction: The preprocessed pose data from each frame is fed into a Convolutional Neural Network (CNN) that captures spatial relationships between body joints, learning posture and body alignment patterns associated with different exercises.

↓

Step6–LSTMTemporalAnalysis:SequentialCNNfeature vectors are passed to a Long Short-Term Memory (LSTM) network that models temporal motion patterns across frames, enabling accurate exercise recognition and repetition counting.

↓

Step 7 – Classification and Counting:Based on learned movement patterns, the system automatically classifies the exercise being performed (squats, push-ups, lunges) and tracks motion cycles to count repetitions accurately in real time.

↓

Step 8 – Posture Analysis:Key joint angles are computed from the detected landmarks and compared with predefined biomechanical reference values to identify incorrect posture or improper movement execution.

Step9–FeedbackGeneration:Whenposturaldeviationsare detected,thesystemdeliversinstantcorrectivefeedbackviavisual on-screenalertsorvoiceprompts(e.g.,“Keepyourbackstraight” or “Bend your knees more”), guiding the user immediately.

Step 10 – Output Display:The interface displays exercise type,repetitioncount,posturefeedbackscore,andaliveskeletal overlay.Operating at over 30 FPS, the system ensures smooth, continuous real-time monitoring.

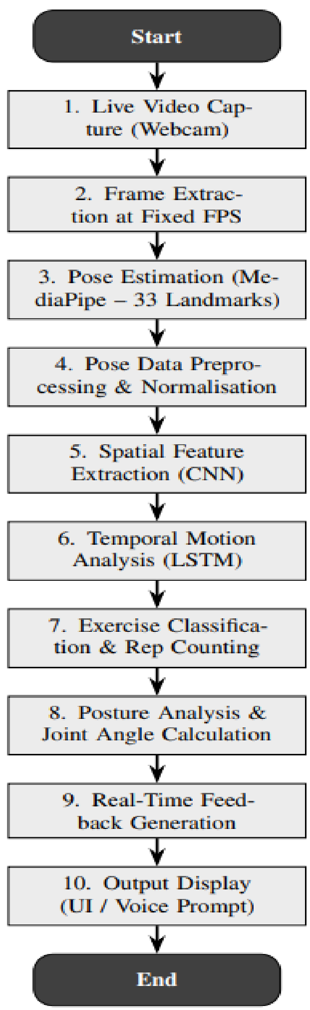
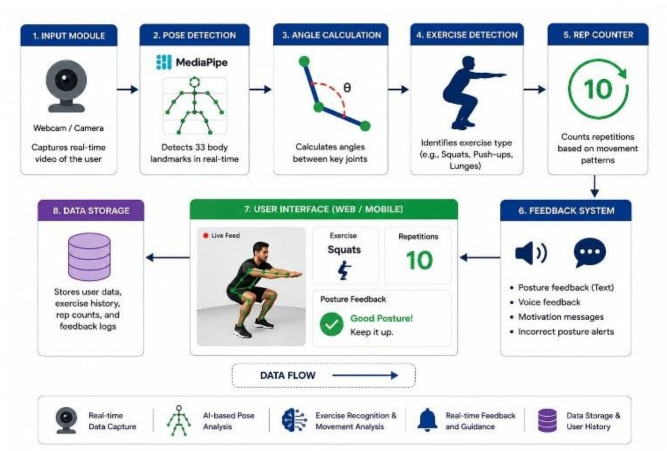


Figure1:AIFitnessTrackerandPostureDetector processing pipeline

V. SYSTEM ARCHITECTURE



VI. IMPLEMENTATION AND EXPERIMENTAL SETUP

A. *Software Stack*

Table 1 summarizes the major technologies and software libraries used in the proposed AI-Based Fitness Tracker and Posture Detection System. These technologies collectively enable real-time pose estimation, exercise recognition, posture analysis, feedback generation, and efficient system deployment**.**

Table1:SoftwareComponentsoftheProposedSystem

Component	Technology/LibraryUsed
PoseEstimation	MediaPipeBlazePose(33Body Landmarks)
DeepLearning Model	TensorFlow/Keras(CNN–LSTM Architecture)
ComputerVision	OpenCV
BackendFramework	Flask,Node.js
FrontendInterface	React(WebApplication),Android (MobileApplication)
Database	MongoDB,Firebase
Programming Language	Python3.9+
VoiceFeedback System	pyttsx3/GoogleText-to-Speech(gTTS)
VersionControl	Git

B. *HardwareConfiguration*

Developmentandtestingwereconductedonasystemequipped with an IntelCorei5(8thgeneration) processor, 16 GBRAM,an integrated GPU capable of running OpenCV and MediaPipe at 20–30FPS,andastandard720pHDwebcamoperatingat30FPS. MobiletestingwasperformedonanAndroiddevice(Snapdragon 730G, 6 GB RAM, 1080p camera).

C. *DatasetandTraining*

TheCNN–LSTMmodelwastrainedonacurateddataset of labelledexercisevideo sequencescovering threeexerciseclasses: squats, push-ups, and lunges. Pose landmark sequences were extracted using MediaPipe from each video and normalized beforetraining.Toimprovemodelgeneralization,augmentation methods such as horizontal image flipping and slight positional variations were applied. The dataset was split 80:10:10 for training, validation, and testing respectively.

D. EvaluationMetrics

System performance was assessed using: (i) Exercise Classification Accuracy — percentage of correctly identified exercise types on the test set; (ii) Repetition Counting Error (RCE)—meanabsolutedifferencebetweensystem-countedand groundtruthrepetitions;and(iii)PostureCorrectionPrecision— proportion of correctly flagged postural deviations compared to expertannotations. correctly flagged postural deviations compared to ex-pert annotations.

VII. RESULTS AND DISCUSSION

A. Exercise Classification

The CNN–LSTM hybrid model achieved an overallexercise classification accuracy of **94.3%** across the three exercise classes on the held-out test set. Table 2 presents per- class performance.

Table2: ExerciseClassificationPerformance

Exercise	Accuracy(%)	F1Score
Squats	95.8	0.96
Push-ups	93.2	0.93
Lunges	93.9	0.94
Overall	94.3	0.94

B. Repetition Counting

The system achieved a mean Repetition Counting Error (RCE) of **0.4 reps** per set across all exercise types, demonstrating high reliability for practical workout tracking.

C. Posture Correction

Posture deviation detection achieved a precision of **91%**and recall of **88%** against expert annotations, confirming that the joint-angle-based analysis is effective at identifying common form errors such as knee cave during squats and hip sag during push-ups.

D. Real-TimePerformance

The integrated pipeline operated at an average of **32 FPS** on the development hardware, satisfying the real-time constraint. MediaPipe's lightweight BlazePose model was instrumental in maintaining this throughput without requiring a dedicatedGPU.

E. Discussion

ThehybridCNN–LSTMarchitectureprovedwell-suitedtothe dual demands of the task: the CNN effectively captures instantaneousjointconfigurationswhiletheLSTMretainsmotion history across frames. Delivering feedback locally withoutcloud inference preserves user privacy and eliminates latency introduced by network round-trips.

Extension to a broader exercise vocabulary and multi-camera setups remains as future work.

VIII. CONCLUSION

This paper presented an AI-based real-time fitness trackerand posture detection system that combines MediaPipe Pose Estimation with a CNN–LSTM deep learning model to deliver professional-quality exercise monitoring using only a standard webcam. The system automatically recognizes exercises, counts repetitions, evaluates joint-angle-based posture correctness, and providesinstantcorrectivefeedbackatover30FPS.Experimental resultsdemonstrateaclassificationaccuracyof94.3%,repetition counting error of 0.4 reps, and posture correction precision of 91%.By requiring no wearable hardware and running entirely on-device, the system makes personalized fitness coaching accessible and affordable to a wide range of users, bridging the gap between home workouts and professional training. The system also demonstrates strong real-time responsiveness and scalability, which makes the framework practical for both web- based and mobile fitness platforms.

IX. FUTUREWORK

Planned extensions to the proposed system include: (i) expanding the exercise vocabulary to cover yoga, weight training,andrehabilitationexercises;(ii)multi-persontrackingto support group workout sessions; (iii) future integration with digitalhealthcarerecordsystemsforphysiotherapyusecases;

(iv) adaptive feedback calibrated to individual biomechanical profiles; (v) deployment on edge devices such as Raspberry Pi forlow-coststandalone operation; and (vi) longitudinal progress tracking with AI-generated personalized workout plans.

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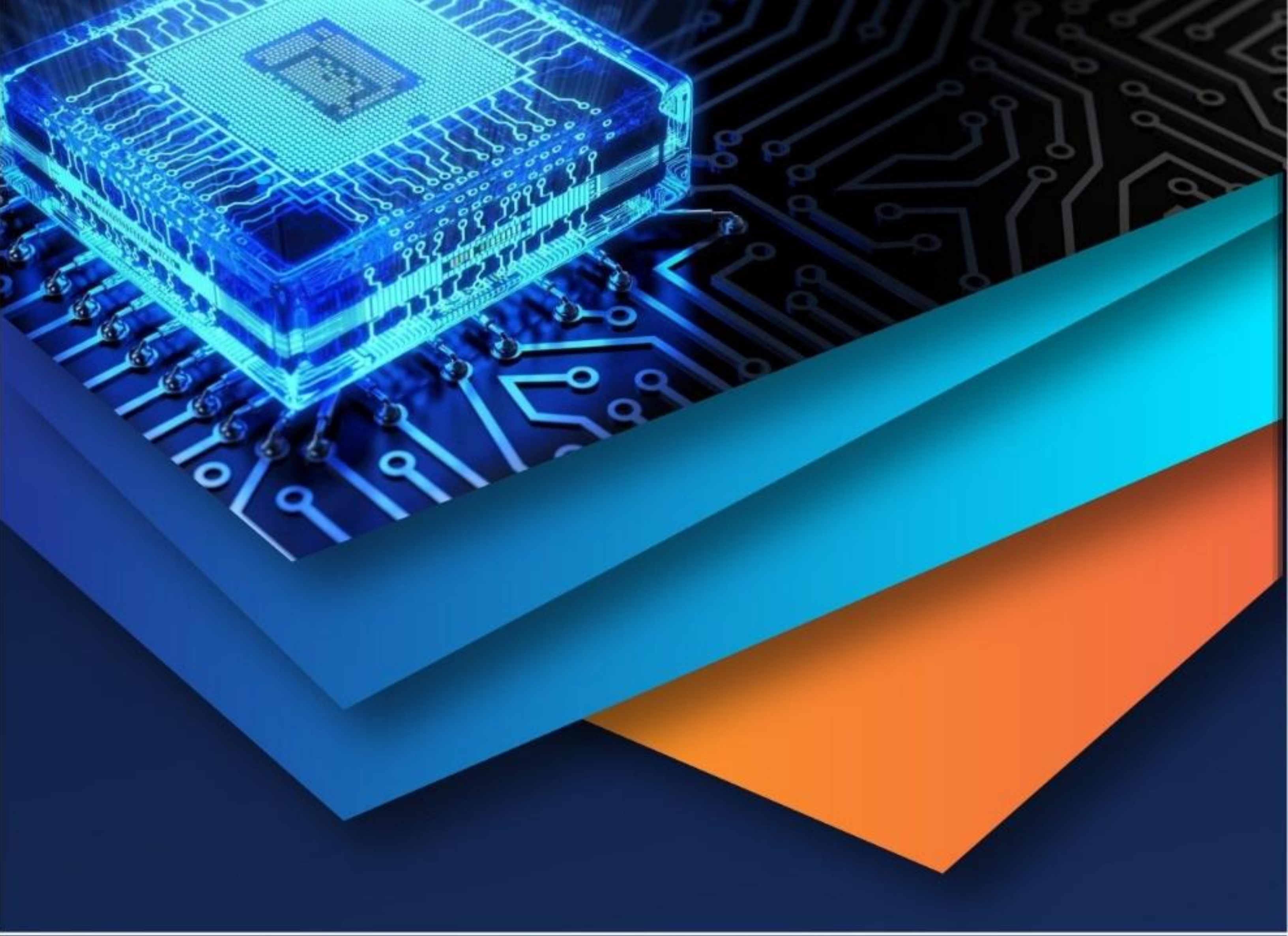

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