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Fit Track - Real-Time Exercise Posture Correction and Performance Monitoring Using Computer Vision

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Abstract*—Incorrectexercisepostureandtheabsenceofreal-timecorrectivefeedbackremainpersistentchallengesinhome-basedfitnes straining, particularly for individuals exercising without professional supervision.Poor exercise form not only diminishes workout effectiveness but substantiallyelevatestheriskofmusculoskeletalinjury. ThispaperpresentsFitTrack,avision-guidedreal-timefitnessmonitoringplatformthat performsautomatedpostureanalysisusinghumanposeestimationandafull-stackwebarchitecture. Thesystemcaptureslivevideoinputtodetectbodykeypoints,computejointangles,andevaluateexerciseformagainstpredefinedbiomechan icalthresholds.Basedonthisanalysis,itdelivers immediate visual and audio corrective feedback, enabling users to adjust their posture during active workout sessions. A finite state machine (FSM)governsrepetitioncountingand movementphasedetection ,whilesessionperformancemetrics—includingpostureaccuracyscoresand repetitioncounts—arepersistedinarelationaldatabase. AhybridAIcoachingengineintegratesGroqAIAPIstodelivercontextual,personalized coaching tips with a local JSON fallback ensuring uninterrupted guidance.Experimental evaluation demonstrates 90% posture detection accuracy and 95% repetition counting accuracy at 15–20 FPS on standard consumer hardware, requiring no wearable sensors or specialized equipment. FitTrackrepresentsanaccessible,low-latency,andtechnicallyrobustsolutionforimprovingworkoutsafety,trainingefficiency,andlong-term user engagement.

Keywords*—HumanPoseEstimation;Real-TimeFeedback;FitnessMonitoring;ComputerVision;MediaPipe;DeepLearning;Full-Stack Web Application; Joint Angle Computation; Repetition Counting; Groq AI; Flask; React.js.

I. INTRODUCTION

Artificial intelligence and computer vision have emerged as transformative forces in modern fitness and health monitoring systems, enabling automated, objective analysis of human movement without reliance on costly or intrusive wearable hardware.The growing adoption of home-based workout routines, accelerated by global shifts toward remote and self-directed fitness, has created compellingdemandforintelligentsystemscapableofprovidingreal-timeexerciseguidance,postureevaluation,andperformance tracking in accessible formats.

Traditional fitness monitoring paradigms depend heavily on wearable inertial sensors, electromyography (EMG) equipment, or direct trainersupervision—resourcesthatarefinanciallyprohibitiveorlogisticallyimpracticalforthemajorityofindividuals. Existing consumer fitnessapplicationshavepartiallyaddressedthisgapbydeliveringactivitytrackingandcaloricestimationfeatures,yet they consistently fail to address a more fundamental concern: the correctness of exercise posture. Improper biomechanical form duringresistanceandbodyweightexercisesdoesnotmerelyreducetrainingeffectiveness;itintroducescompoundinginjuryrisksto joints, tendons, and skeletal structures that manifest gradually and may cause lasting damage.

Recent advances in deep learning-based human pose estimation have enabled accurate, real-time skeletal landmark detection directlyfrommonocularRGBvideostreams,eliminatingtheneedforspecializeddepthcamerasorphysicalmarkers.Frameworks suchas Media PipeBlazePoseproviderobust33-keypointskeletalrepresentationsatframeratessuitableforinteractiveapplications, opening a viable pathway toward camera-only posture analysis systems deployable on commodity hardware.

Motivatedbythesedevelopments,thisworkpresentsFitTrack—avision-guided,full-stackfitnessmonitoringplatformintegrating pose estimation, biomechanical joint angle computation, rule-based posture evaluation, and a hybrid AI coaching engine.The systemoperates entirelyonstandard camera-enabledconsumerdevices,deliveringreal-timecorrective feedbackthroughcombined visual and audio modalities while maintaining persistent session analytics for longitudinal performance tracking.

FitTrack delivers four key contributions: a markerless real-time fitness monitoring system eliminating dependency on wearable sensorsdeployableonstandardconsumer-gradedevices,avectordot-product-basedjointanglecomputationmodelappliedto

MediaPipe BlazePose keypoints for dynamic per-frame posture correctness evaluation, a finite state machine (FSM) for precise repetition counting and movement phase detection integrated with visual and audio feedback, and a full-stack web platform combiningaReact.jsfrontend,FlaskAPIbackend,PostgreSQLsessiondatabase,andaGroqAI-poweredcoachingengine withlocalJSONfallback—experimentallyvalidatedat90%posturedetectionaccuracy,95%repetitioncountingaccuracy,and 15–20 FPS real-time performance on consumer hardware.

II. MOTIVATION AND PROBLEM STATEMENT

Despite the proliferation of fitness applications and wearable health devices, a fundamental gap persists in current workout monitoring systems: the inability to evaluate and correct exercise form in real time.This limitation has direct implications for trainingsafetyandeffectiveness,particularlyforthegrowingpopulationofindividualsexercisingindependentlyathomewithout qualified coaching.

Existingplatformsoverwhelminglyprioritizeoutcomemetrics—stepcounts,caloricexpenditure,heartratezones—whiletreating exercise executionqualityasasecondaryorentirelyignoredconcern. Posturecorrectnessduringcompoundmovementssuchas squats, push-ups, and bicep curls is biomechanically critical; deviations from proper joint alignment at high repetition volumes create cumulativestresspatternsthatpredisposeindividualstoinjury. Pre-recordedinstructionalcontentprovidesnomechanism for detecting or correcting form deviations as they occur in real exercise sessions.

The dependency on wearable sensors in more sophisticated monitoring systems introduces additional barriers — financial cost, calibrationrequirements,andphysicalinconvenience—thatlimitaccessibilityforcasualandintermediatefitnesspractitioners.A purelyvision- based approach,leveragingubiquitousbuilt-inorexternalcamerasalreadypresentinmosthomeenvironments,offers a path toward removing these barriers entirely.

FitTrack was developed to address this precise problem:the need for a system that evaluates not merely whether exercise is occurring,butwhetheritisbeingperformedcorrectly,andthatdeliversactionablecorrectiveguidancewithsufficientimmediacyto influenceuserbehaviorwithinthesameexerciserepetition. Theplatformencodesbiomechanicalknowledgeintoprogrammable evaluation logic, making expert-level posture assessment continuously available to any user with a camera-enabled device.

III. LITERATURE REVIEW

The application of artificial intelligence and computer vision to fitness monitoring has attracted sustained research interest, with humanposeestimationestablishingitselfasafoundationaltechniquefornon-invasivemovementanalysis. Theliteraturereveals meaningful progressacrossseveraltechnicaldimensionsalongsidepersistentlimitationsthatmotivatethedevelopmentofFitTrack.

Chen et al.[1] proposed an exercise assessment framework combining human pose estimation with relative phase analysis for remotemonitoringcontexts. Theirsystemdemonstratedhighaccuracyinquantifyingmotionqualityandestablishedtheviability of camera-based exercise evaluation without wearable instrumentation. However, the architecture was oriented toward post-hoc performanceassessmentratherthanthedeliveryofcontinuouscorrectivefeedbackduringactiveexerciseexecution—adistinction with direct implications for injury prevention and behavioral correction.

Deeplearningapproacheshavesubstantiallyadvancedtheprecisionofpostureclassification.WorkbyNguyenetal.[2]employed deepneural networksandsupportvectormachinestoclassifyexercisemovementsanddetectincorrectpostures,achievingstrong classification performance. While technically rigorous, such systems function primarily as binary correctness detectors without providing users with joint-level corrective guidance necessary to remediate form deficiencies in real time.

Vision-basedanddepth-sensingmodalitieshavebeenexploredtoextendposeestimationtothree-dimensionalrepresentations.Wang etal.[3]investigatedRGBD-based3Dhumanposeestimationforfitnessassessmentusingdepthcameras,demonstratingimproved spatialaccuracy comparedtomonocularRGBapproaches. Comparable3Destimationcapabilitieshavebeendemonstratedusing MediaPipein combinationwithPython-basedinferencepipelines[4],offeringrobustlandmarkdetectionwithoutdepthhardware. Both directions either impose hardware constraints that reduce accessibility or lack the full-stack web integration necessary for practical home deployment.

AI-drivenvirtualcoachingsystemsrepresentamoreholisticapproach. Al-awadhietal. [5]developedadeeplearning-basedvirtual gymtrainerprovidingreal-timeexerciseguidanceandformcorrection,demonstratingthefeasibilityofintegratingposeanalysis withdynamicinstructionalcontent.Thechallengeofdeliveringlow-latencyvisualandaudiofeedbackthroughasingleaccessible web interface without requiring specialized hardware remains insufficiently addressed in existing literature.

TheMediaPipeframework[6]providesthefoundationalposeestimationinfrastructureunderlyingFitTrack,offering33-keypoint skeletal detection optimized for CPU-bound consumer hardware.Classical pose estimation work by Cao et al.

[7], using part affinity fieldsformulti-person2D estimation,establishedkeyalgorithmic foundationsforsubsequentlightweight implementations.

The importance of real-time corrective feedback has been underscored by Dewang et al.[8], who demonstrated measurable performanceimprovementswhenusersreceiveimmediatepositionalguidanceduringsquatexecution.NVIDIA’sDeepStreamSDK [9] illustrates the broader industrial trajectory toward real-time pose inference on commodity hardware, validating the architectural feasibility of FitTrack’s approach.

In summary, the existing literature confirms that individually, pose estimation, posture classification, and AI coaching are technicallymaturecapabilities.Theunaddressedchallenge—andthespaceFitTrackoccupies—istheirintegrationintoaunified, accessible, real-time platform that delivers joint-level corrective feedback through a browser-accessible interface, without hardware dependencies, and with persistent performance analytics for longitudinal user tracking.

IV. PROPOSED SYSTEM

FitTrack is structured as a four-component full-stack architecture comprising a React.js user interface, a Flask API backend server,anAIengineintegratingposeestimationandworkoutanalysismodules,andaPostgreSQLrelationaldatabaseforsession persistence. Dataflowsunidirectionallyatexecution:user-initiatedvideostreamsaretransmittedtothebackend,processedthrough the AI engine pipeline, and results are returned to the frontend alongside persistent storage of session metrics.

A. System Architecture Overview

The user interface captures live camera input and communicates with the backend exclusively through REST API endpoints, ensuringa stateless,scalableclient-server boundary. Thebackend functionsasa lightweightorchestrationlayer,receiving video frame data, invoking pose estimation and angle computation logic, and managing database read/write operations. A hybrid AI coaching engine calls Groq AI APIs for contextual, profile-aware coaching content during connected sessions, with automatic fallback to a curated local JSON tip database to guarantee uninterrupted guidance under degraded network conditions.

B. System Workflow

TheoperationalworkflowofFitTrackbeginswithcontinuouscaptureoflivevideoframesfromtheuser’scameradevice. Frames are transmittedtotheFlaskbackendviaRESTAPIcalls,wherepreprocessing—includingresizingandnormalization—isapplied priortoinference.ThepreprocessedframesareprocessedbytheMediaPipeBlazePosemodel,whichextracts33skeletalkeypoints per frame representing the full-body landmark topology.

Extracted keypoint coordinates are passed to the joint angle computation module, which calculates relevant joint angles for the selectedexercise.Computedanglesareevaluatedagainstexercise-specificthresholdrangesbythedecisionlogicmodule,producing a per-frame posture correctness classification.The FSM-based repetition counter tracks movement state transitions to detect completed repetitions accurately. Corrective feedback is generated and transmitted back to the frontend for immediate display, while session metrics including repetition count, posture accuracy scores, and session duration are written to the PostgreSQL database for longitudinal analytics.

V. METHODOLOGY

The proposed system follows a structured pipeline to perform real-time exercise posture analysis and feedback generation. The methodology consists of multiple stages, including data acquisition, pose estimation, joint angle calculation, decision logic, and feedback generation.

A. Data Acquisition

ThesystemoperatesonlivevideoinputcapturedviaastandardRGBcameraconnectedtotheuser’sdevice.Eachframeisextracted from the continuous video stream and processed individually to support real-time inference. Preprocessing operations — spatial resizing to the model’s required input resolution and pixel value normalization — are applied uniformly to ensure consistency across varying camera configurations and reduce computational overhead in downstream inference stages.

B. PoseEstimation

HumanposeestimationisperformedusingtheMediaPipeBlazePosetopology,adeeplearning-basedmodelcapableofdetecting 33 full-body skeletal landmarks per frame at real-time frame rates on CPU-class hardware.

The model identifies anatomically significant keypoints including bilateral shoulder, elbow, wrist, hip, knee, and ankle landmarks, producing a normalized 2D coordinaterepresentationoftheuser's skeletalconfiguration foreachprocessedframe. Thesecoordinatesconstitutetheinputtothe joint angle computation pipeline.

C. JointAngleCalculation

Exercise posture is evaluated through the computation of joint angles at anatomically relevant joints using the detected keypoint coordinates.ForthreekeypointsA(x_1,y_1),B(x_2,y_2),andC(x_3,y_3),whereBrepresentsthevertexjointofinterest,thevectors originating from B toward A and Care defined as:

$$\vec{BA}=(x_1-x_2,y_1-y_2) \quad (1)$$

$$\vec{BC}=(x_3-x_2,y_3-y_2) \quad (2)$$

ThejointangleθatBiscomputedusingthedotproductformulation:

$$\theta=\arccos\frac{\vec{BA}\cdot\vec{BC}}{|\vec{BA}||\vec{BC}|} \quad (3)$$

Thecomputedangleθ isevaluatedcontinuouslyagainstexercise-specificthresholdrangestodetermineposturecorrectnessona per-frame basis, enabling detection of deviations within the temporal resolution of a single video frame.

D. DecisionLogicandRepetitionCounting

Posture classification employs threshold-based decision logic in which each supported exercise has predefined acceptable joint angle ranges derived from established biomechanical guidelines.A frame is classified as correct posture if all monitored joint angles fall within their respective acceptable ranges; deviation of any monitored angle beyond its threshold triggers an incorrect posture classification for that frame.

Repetitioncountingisimplementedthroughafinitestatemachine(FSM)thatmodelsthediscretemovementphasesofeachexerciseforexample,the DOWNandUPphasesofabicepcurl,ortheSTANDINGandSQUATphasesofasquat. Statetransitionsare triggeredbythreshold crossingsinthemonitoredjointangle,ensuringthatonlybiomechanicallycompletemovementcyclesare registered as valid repetitions, preventing erroneous counting of partial or false movements.

E. FeedbackGenerationandPerformanceTracking

Upon posture classification, the system generates multi-modal feedback.Visual feedback is rendered as on-screen overlay annotations including color-coded joint indicators, posture score displays, and directional correction prompts. Audio feedback delivers spoken alerts when incorrect posture is detected, providing corrective cues without requiring the user to divert visual attention.Postureaccuracyiscomputedastheproportionofcorrectlyclassifiedframesacrossthesession,expressedasanormalized scorefrom0to100. Sessionmetrics—repetitioncount,accuracyscore,exercisetype,andsessionduration—arepersistedtothe PostgreSQL database at session completion, enabling longitudinal performance analytics through the FitTrack dashboard.

VI. IMPLEMENTATION

Theproposedsystemisimplementedusingafull-stackarchitecturethatintegratesmodernwebtechnologieswithcomputervision frameworks to enable real-time fitness monitoring.

A. FrontendWeb Platform (React.js)

The FitTrack web application delivers a comprehensive fitness management experience engineered for zero-hardware-dependency operation. The frontend is implemented in React.js and communicates with the backend via REST APIs to ensure low-latency interaction. The platform exposes four principal functional modules:

- MainDashboardandAnalytics:Dynamicallypollsthebackendtovisualizekeyperformanceindicatorsincludingcumulative calories burned, activity streaks, and daily progress metrics through interactive chart components.
- FormAnalysisModule:Providesexerciseselectioncontrols,afour-stepguidedusageworkflow,anddedicatedtrackingpanels evaluatingPoseDetectionaccuracy,RangeofMotioncompliance,andRepQualityScores,backedbyaPostgreSQLsession history log.
- Groq-Powered Diet and Nutrition Engine:Leverages Groq AI APIs to generate fully personalized daily meal plans dynamically, computing caloric and protein targets from user biometrics and providing time-structured nutritional schedules tailored to individual fitness goals.

- AI Coaching System: Injects user profile data — experience level, training goals, and dietary restrictions — into structured prompt templates, querying Groq AI to surface context-aware training and recovery tips dynamically during each session.

B. BackendServerandCVEngine

Theserver-sidebackendisimplementedusingtheFlaskframework,servingasalightweightRESTAPIlayerbetweentheReact.js frontendandtheAIprocessingmodules. OptimizedRESTendpointshandlecontinuousframetransmissionandpostureanalysis requests with minimized serialization overhead to sustain real-time performance targets.

The core pose estimation pipeline employs the MediaPipe BlazePose model for 33-keypoint skeletal extraction, with OpenCV handling frame preprocessing, bounding box rendering, and visual overlay generation.Extracted keypoint coordinates feed directly intothejointanglecomputationmodule.DatapersistenceismanagedthroughaPostgreSQLrelationaldatabasestoringuser profiles, exercise session logs, per-session repetition counts, and posture accuracy metrics, enabling structured querying for the dashboard analytics layer.

Thecompletesystemwasdevelopedandevaluatedonalocalmachineequippedwithan IntelCorei5processorand8GBRAM, using a standard 1080p webcam as the sole input device.By employing lightweight inference techniques and efficient REST communication, FitTrack achieves real-time performance without GPU acceleration or specialized compute hardware.

VII. RESULTS AND DISCUSSION

The proposed system was experimentally evaluated based on posture detection accuracy, repetition counting performance, and real-timeprocessingcapability. Thesystemwastestedacrossbicepcurls,squats,andpush-upsundervaryinglightingconditions and background environments.

Metric	Value
Posture Detection Accuracy	90% Repetition Counting Accuracy 95% FrameRate 15–20FPS
SystemLatency	<1second

TABLEI.PerformanceEvaluationofFitTrackSystem

The system achieved a posture detection accuracy of 90%, correctly identifying correct and incorrect exercise forms across the evaluatedexerciseset. Repetitioncountingaccuracyreached95%,demonstratingreliableFSM-basedmovementphasedetection underreal-worldconditions.Theprocessingpipelinesustainedanaverageframerateof15–20FPSwithend-to-endsystemlatency below 1 second, satisfying the responsiveness requirements for real-time corrective feedback.

Poseestimationperformanceremainedconsistentundermoderatelightingvariationanddiversebackgroundconditions.Accuracy degradationwasobservedincasesofsignificantpartialocclusion—forexample,whenlimbswerepositionedoutsidethecamera frame — representing an expected limitation of monocular 2D pose estimation that depth-sensing approaches partially mitigate. Overall,theresultsindicatethattheproposedsystemiscapableofprovidingaccurate,efficient,andreal-timefitnessmonitoring.

Ref.	Method	RTFeedback	Wearable-Free
[1]	Pose&Phase	No	Yes
[2]	DeepNN	No	Yes
[3]	RGBDPose	Partial	Yes
Ours	AI&Pose	Yes	Yes

TABLEII. ComparisonwithExistingFitnessMonitoringSystems

A. PoseEstimationOutputs

Real-timefeedbackmechanismswerevalidatedacrossmultipleexercisetypesthroughlivesystemtesting. Bicepcurlevaluation demonstrated accurate FSM state transitions between the DOWN phase (elbow angle approximately 169°) and UP phase (elbow angleapproximately100°),withcorrectrepetitionincrementsateachfullmovementcycle.

Squatevaluationcapturedthestanding initialization phase at 168°and tracked the descent phase at 158°, with amber-coded feedback correctly activated during the transitionphase. Push-upevaluationdemonstratedthesystem'sreal-timeerrordetectioncapability: upondetectionofhipsag—an angulardeviationfromneutralspinalalignment—theposturescoredroppedto22/100andacorrectivealertwastriggered;asthe user rectified spinal alignment, the score recovered to 34/100 within the same repetition cycle.

VIII. CONCLUSION

ThispaperpresentedFitTrack,areal-timevision-guidedfitnessmonitoringplatformdesignedtoimproveexerciseposturesafety andprevent traininginjurieswithoutdependencyonwearablesensorsorspecializedhardware.ByintegratingMediaPipeBlazePose pose estimation, vector-based joint angle computation, FSM-driven repetition counting, and a hybrid Groq AI coaching engine within a full-stack web architecture, FitTrack delivers accurate, low-latency posture analysis and immediate corrective feedback accessiblefromanystandardcameraenableddevice.Experimentalevaluationconfirmed90%posturedetectionaccuracy,95%repetitioncountingaccuracy,andreal-timeperformanceat15–20FPSonconsumerhardware,establishingFitTrackasatechnically sound and practically accessible solution for home-based workout monitoring.

Futuredevelopmentwillprioritizeexpandingtheexerciselibrarytoencompasscomplexmulti-jointmovementsincludingdeadlifts, overhead press, and lateral movements.Integration of personalized AI-driven adaptive training plans — adjusting exercise parametersbasedonhistoricalperformancetrajectories—willfurtherenhancecoachingvalue.PortingFitTracktoanativemobile applicationandincorporating smartwatch APIintegration forreal-timevitalsignmonitoring, includingheartrateandblood oxygen saturation, will extend the platform's physiological monitoring scope and user engagement potential.

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