

SMART FITNESS TRAINER USING AI-BASED POSE ESTIMATION

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ABSTRACT

The rapid growth of artificial intelligence and computer vision has enabled the development of intelligent fitness applications that provide real-time feedback and personalised training. This paper presents a Smart Fitness Trainer using AI-Based Pose Estimation, designed to help users perform exercises with correct posture and reduce the risk of injury. The proposed system utilises Google ML Kit's pose detection to identify key body joints and analyse user movements through a smartphone camera in real time. The application is developed using Flutter for cross-platform support and Firebase for user authentication, data storage, and progress tracking. In addition to posture detection, the system integrates features such as a BMI calculator, food chart, and exercise recommendations to promote overall health awareness. Instant feedback is provided to guide users during workouts, while gamified elements encourage consistency and motivation.

Keywords: Artificial Intelligence, Pose Estimation, Computer Vision, Smart Fitness Trainer, Real-Time Posture Detection, Google ML Kit, Flutter, Firebase, Mobile Health Applications, Exercise Monitoring

I.INTRODUCTION

The rapid advancement of artificial intelligence (AI) and computer vision technologies has significantly influenced the development of intelligent healthcare and fitness applications, enabling automated monitoring and personalised guidance for users. With the increasing popularity of home-based workouts and mobile fitness applications, many individuals perform exercises without professional supervision, which often results in incorrect posture, reduced workout effectiveness, and a higher risk of musculoskeletal injuries. AI-based pose estimation provides an effective solution by detecting key human body joints and analysing movement patterns through standard smartphone cameras, eliminating the need for specialised sensors or wearable

devices. The proposed system is developed using Flutter to support cross-platform mobile environments and Firebase for secure user authentication, data storage, and progress tracking, while Google ML Kit is utilised for accurate and efficient pose detection. In addition to exercise monitoring, the application integrates supportive health features such as a Body Mass Index (BMI) calculator and a food chart to promote balanced nutrition and healthy lifestyle habits.

II.BACKGROUND STUDY

In recent years, AI-powered systems have enabled intelligent human-computer interaction, particularly in motion tracking and posture analysis. Pose estimation technology plays a vital role in this domain by identifying key human body landmarks such as joints and angles from images or video

streams. Modern frameworks like Google ML Kit provide real-time body landmark detection using standard smartphone cameras, eliminating the need for specialised hardware sensors.

With the growing adoption of mobile technologies, cross-platform development frameworks such as Flutter have enabled the creation of efficient, responsive fitness applications that run on both Android and iOS. Additionally, cloud-based backend services such as Firebase support real-time data storage, authentication, and user progress tracking, making personalised health monitoring more accessible and scalable. Traditional fitness training often requires personal trainers to guide users in maintaining correct posture during workouts. Incorrect posture can lead to muscle strain, joint injuries, and reduced workout effectiveness. While several fitness applications exist, many lack real-time corrective feedback and advanced posture validation mechanisms. AI-based pose estimation addresses this limitation by analysing joint coordinates, calculating angles, and comparing them with predefined reference poses to detect deviations instantly. Recent research in human activity recognition and motion analysis highlights the importance of real-time key point detection, frame-by-frame angle computation, and machine learning-based classification techniques for exercise validation

III. MACHINE LEARNING TECHNIQUE FOR POSE DETECTION

The proposed Smart Fitness Trainer system uses a Supervised Deep Learning-based 2D Human Pose Estimation technique for detecting and correcting exercise posture in real time. At the core of the system is Google ML Kit, which internally relies on a

(CNN) architecture optimized for mobile devices.

1. SUPERVISED LEARNING

In this project, Supervised Learning plays a central role. It is the quiet teacher behind the scenes. The model did not just wake up one day and understand human posture. It was trained. Carefully. During training, thousands of human body images were used, where each joint shoulders, elbows, hips, knees was already labelled with exact coordinates. Someone had marked them. Precisely. The system learned from those labelled examples. That is the essence of supervised learning. Input image goes in. Correct key points were given. The model tries to predict. It makes mistakes. It adjusts. It learns again. When a user performs an exercise in front of the camera, the trained model predicts the 2D coordinates of each joint. It does not guess randomly. It predicts based on what it has seen before. Similar patterns. Similar body alignments. If the posture slightly deviates, the system still recognises it. Because it has learned variations too.

2. CNN – based pose detection

At the heart of this project lies Deep Learning. Not the buzzword kind. The practical one. The system uses a Convolutional Neural Network (CNN) to understand human posture from raw camera frames. The CNN processes every incoming frame in real time. Around 30 frames per second. Sometimes slightly fluctuates depending on device performance. Each frame passes through multiple layers: convolution, activation, and pooling. Features become more abstract as they move deeper into the network. Early layers detect simple lines. Deeper layers detect meaningful structures. Finally, the output layer predicts 2D coordinates of body landmarks.

3. KEYPOINTS DETECTION AND ANGLE CALCULATION

Using **Google ML Kit**, the model first detects key points on the human body. Small dots. Important ones. Shoulder. Elbow. Wrist. Hip. Knee. Ankle. Each point is predicted with (x, y) coordinates and a confidence score. If the score is high, the system feels confident. If it drops, it becomes slightly unsure. Once the key points are identified, the real math begins. Not heavy. But precise. The system connects three related joints to form two vectors. For example, shoulder–elbow–wrist. These vectors are used to calculate the joint angle using trigonometric formulas. Cosine rule. Dot product. Basic vector mathematics, but applied in real-time. Frame by frame.

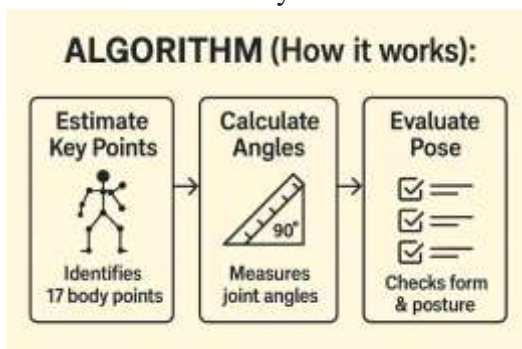


Fig 1.1 ML Techniques for pose detection.

IV. CHALLENGES

The biggest challenge was real-time pose detection. The model must process frames continuously. No lag. No freeze. Around 30 FPS. Sometimes the device slows down, especially on mid-range mobiles. Performance slightly drops. And accuracy may be reduced. Lighting conditions created another problem. Bright light. Dim rooms. Shadows. The camera sees differently in each situation. The pose detection module using Google ML Kit works well, but not perfectly, in extreme conditions. If the background is messy, the key points may shift a little bit. Just a few pixels. But that small shift affects angle calculation. Then come body variations. Every person is different. Height varies. Weight differs. Flexibility changes. A posture

that looks correct for one user may slightly differ for another. Setting fixed angle thresholds was tricky. Too strict? It keeps warning the user unnecessarily. Too loose? It misses incorrect posture. Finding balance was difficult. Camera positioning was another issue. If the phone angle is wrong, the side view becomes the front view. Some joints get hidden. Occlusion happens. When one body part blocks another, detection confidence reduces.

PAPER NAME	AUTHOR(S)	YEAR	TECHNIQUES	MERITS	DEMERITS
Exercise Assessment Based on Human Pose Estimation and Relative Phase for Real-Time Remote Exercise System.	Yeongju Woo and Hieyong Jeong.	2025	Relative Phase, Velocity-based Exercise Posture, Human Pose Estimation and Future Extraction.	Combines human pose estimation (HPE) with a relative phase technique to assess velocity-based exercise posture.	Validation was conducted on a limited dataset.
A Survey of Human-Object Interaction Detection with Deep Learning.	Geng Han, Jiachen Zhao, Lele Zhang and Fang Deng.	2025	Deep Learning, Visual Relationship Detection, Human-Object Interaction	These achieve state-of-the-art accuracy and real-time performance due to their end-to-end nature and powerful global feature modelling.	Occlusions, lighting changes, deformation, and clutter in natural scenes introduce noise that complicates HOI detection
3D Knee and Hip Angle Estimation With Reduced Wearable IMUs via Transfer Learning During Yoga, Golf, Swimming, Badminton, And Dance	Jinxuan Li, Kezhe Zhu, Dongxuan Li, Peiqi Kang, Peter B. Shull	2024	Deep Learning, Prosthesis, Activity Recognition, Reduced Sensor Set, Transformer	Unlike most prior works centred on walking (yoga, golf, swimming simulation, badminton, dance).	Estimation is less accurate in hip adduction and internal/external rotation angles compared to flexion/extension.
Video-Based Fall Detection Using Human Pose and Constrained Generative Adversarial Network	Lian Wu, Chao Huang, Lunke Fei, Shuping Zhao, Jianchuan Zhao, Zhongwei Cui and Yong Xu	2024	Fall Detection, Human Pose, Pose Image Prediction, Unsupervised Learning	The fall detection uses relative movement of key joints and balance-related dynamic descriptors derived from pose estimation.	Although the approach aims to overcome generalisation challenges inherent in simulated vs real elderly falls.
Classification of Surya Namaskar Yoga Asanas: A Sequential Combination of Predominant Poses For Physical and Mental Health	Venkatesh Bhandage, Srikanth Prabhu, Balachandra S. Hadimani, krishnaraj Chadaga, Niranjana Sampathila, Sucharitha Shetty	2024	ANN, CNN, KNN, HOG, SURF, Surya namaskar, yoga	The authors developed a novel dataset specifically for Surya Namaskar poses with images from 10 performers and 1200 images.	The method was tested on static images, with no exploration of real-time pose recognition.

V.CONCLUSION AND FUTURE WORK

The Smart Fitness Trainer using AI-based pose estimation successfully addresses the problem of incorrect exercise posture by providing real-time monitoring and instant feedback. The system utilises advanced technologies such as Google ML Kit, Flutter, and Firebase to deliver accurate pose detection and a user-friendly interface. It helps users perform exercises safely, improves workout efficiency, and reduces the risk of injuries. The implementation of features like BMI calculation, exercise tracking, and guided workouts makes the application a complete fitness solution.

Modern fitness apps often lack real-time feedback and personalised guidance, leading to incorrect posture, ineffective workouts, and inconsistent health tracking. This project aims to solve these issues by integrating AI-based pose estimation, biometric analysis, and nutrition tracking into a unified mobile platform.

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Future upgrades include voice-guided sessions and wearable device integration. Adaptive workout plans based on user performance can improve personalisation. Gamification features like badges and

challenges will boost engagement. Offline mode will support users in areas with low connectivity. Predictive analytics may help prevent injuries and optimise health outcomes.

VI.REFERENCES

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