Machine Learning for Exercise Form Correction using Pose Detection and Camera Tracking

Ankith Goswami, Computer Systems Engineering
Mentor: Dr. Chao Wang
Arizona State University, Ira Fulton Schools of Engineering

Background and Motivations:

Problem in the Gym:
Many people experience pain or injury from exercising with poor form. This discourages consistent training and can lead to long-term health issues.

Solution:
Personal trainers can be expensive, but recent advances in machine learning and pose detection allow us to build virtual coaching tools that are more accessible.

Why It Matters:
By giving real-time feedback using only a camera, this project aims to reduce injuries, improve gym performance, and support long-term fitness goals—all while aligning with FURI's focus on technology-enhanced health.

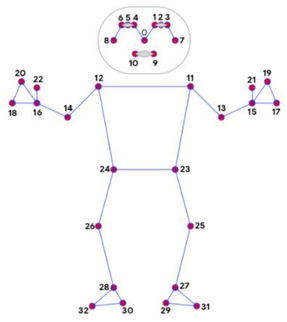
Research question:

What machine learning techniques and models can be used to create a real-time algorithm that corrects exercise form using pose detection and camera tracking?

Methodology :

Pose Detection:
Used Media Pipe Pose and Google ML Kit to extract 33 body landmarks from recorded exercise videos showing correct and incorrect form.
Still Image Form Classification:
The model detects and classify exercise form (correct vs. incorrect) through still images using body landmark data. This allows immediate analysis without delays, enhancing user engagement and training accuracy.
Software:
Python: Primary programming language used for scripting the entire pipeline —from pose detection to data processing and visualization.
Media Pipe Pose (by Google): Provided real-time pose estimation with 33 key body landmarks. Essential for detecting joint positions during exercise movement.

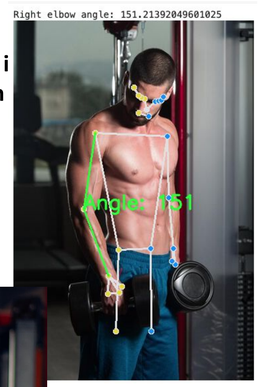
Pose estimation uses a 33-point landmark model from Media Pipe and OpenCV to map and analyze human movement for form correction.

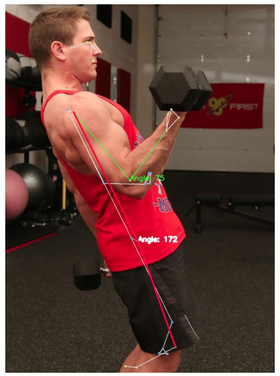


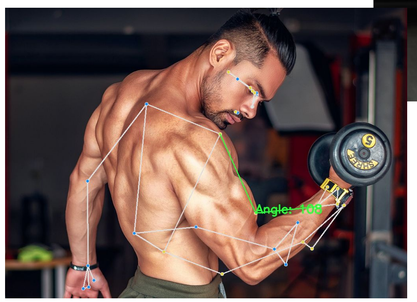
0. nose
1. left_eye_inner
2. left_eye
3. left_eye_outer
4. right_eye_inner
5. right_eye
6. right_eye_outer
7. left_ear
8. right_ear
9. mouth_left
10. mouth_right
11. left_shoulder
12. right_shoulder
13. left_elbow
14. right_elbow
15. left_wrist
16. right_wrist
17. left_pinky
18. right_pinky
19. left_index
20. right_index
21. left_thumb
22. right_thumb
23. left_hip
24. right_hip
25. left_knee
26. right_knee
27. left_ankle
28. right_ankle
29. left_heel
30. right_heel
31. left_foot_index
32. right_foot_index

Results:

These pictures shows good form as i grabs the angle of your bicep curl in full extension and curled.







This picture shows a red line over the form indicating wrong form which make the model find bad form specifically

Future Goals:

Live Real-Time Feedback System:
While current results focus on pose classification and visual cues, the next step is to implement a fully responsive system that gives audio or on-screen feedback as users move, enabling instant corrections during exercise.
Rep Counting & Exercise Tracking:
A future goal is to track repetition counts and exercise sets using motion patterns and pose cycles. This would help users monitor their progress automatically, providing detailed workout logs without manual input.
Preprocessing:
Split videos into frames, normalized landmark data, and labeled samples by form type.
Model Integration:
Applied pretrained CNN and LSTM models (no custom training) to classify form quality based on spatial and sequential pose patterns.
Visual Feedback with Red & Green Lines:
Correct movements are highlighted with green lines, while incorrect movements trigger red lines over joints or limbs. This intuitive color-coded feedback helps users quickly recognize and adjust improper form.
Image Overlay Functionality:
Pose lines are drawn directly on live video or recorded frames to show form in context. These visuals serve as clear guidance, mimicking how a trainer might demonstrate to show proper alignment .
These features were outside the current scope due to time constraints but are planned for future changes to the project.

Acknowledgements:

Prof. Chao Wang: Big thankyou to my faculty mentor for guiding the project's organization and planning, holding me accountable each week to ensure steady progress and clear milestones.
Devesh Nath: Big thanks to Devesh Nath for fueling parts of the project with innovative ideas and helping drive its progression forward.

Cited Sources:

Jiang, X., Hu, Z., Wang, S., & Zhang, Y. (2023). A Survey on Artificial Intelligence in Posture Recognition. Computational Modeling in Engineering & Sciences, 137(1), 35–82. https://doi.org/10.32604/cmes.2023.027676
Stenum, J., Cherry-Allen, K. M., Pyles, C. O., Reetzke, R. D., Vignos, M. F., & Roemmich, R. T. (2021). Applications of Pose Estimation in Human Health and Performance Across the Lifespan. Sensors, 21(21), 7315. https://doi.org/10.3390/s21217315
Arrowsmith, C., Burns, D., Mak, T., Hardisty, M., & Whyne, C. (2023). Physiotherapy Exercise Classification with Single-Camera Pose Detection and Machine Learning. Sensors, 23(1), 363. https://doi.org/10.3390/s23010363
Xia, D. X., Su, S. Z., Geng, L. C., et al. (2017). Learning Rich Features from Objectness Estimation for Human Lying-Pose Detection. Multimedia Systems, 23, 515–526. https://doi.org/10.1007/s00530-016-0518-5
MediaPipe by Google. Pose Estimation Documentation. https://developers.google.com/mediapipe/solutions/vision/pose_landmarker

FURI

Ira A. Fulton Schools of Engineering
Arizona State University