Deadlift Decoded: An AI Approach to Perfecting the Pull

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ABSTRACT

Proper exercise form is crucial for maximizing workout effectiveness and minimizing injury risk. The deadlift, a key compound movement, carries a particularly high risk of injury when performed incorrectly. Since access to trainers—and the real-time feedback they provide—is often limited, lifters frequently struggle to identify issues with their technique and lack guidance on how to correct them. This project is considered high risk due to its ambitious scope and the scarcity of suitable exercise video datasets for deadlift analysis.

1 INTRODUCTION

In this paper, we investigate the feasibility of an AI-powered system that utilizes a custom-trained model, pose estimation, and machine learning to enhance an athlete's form and minimize injury risk.

The deadlift is a fundamental strength training exercise, renowned for its ability to build muscle, improve core stability, and improve functional fitness. However, due to its technical complexity, improper deadlift form is commonly observed, especially among beginner trainees. Poor form in any exercise can cause serious injuries, but with deadlifts, the lower back, hips, and knees are particularly at risk. Lower back pain often results from rounding the back during lifts, which places excessive stress on the spine, while hamstring strains can occur when the hamstrings are too weak or overexerted, similar to overstretching a rubber band [3].

Research underscores the prevalence of these injuries in powerlifting. Studies show that approximately 43% of powerlifters experience lower back injuries at some point in their fitness journey. [3]. These statistics highlight the critical need for proper deadlift technique to prevent chronic pain and long-term mobility issues.

Gym athletes often lack immediate or professional feedback on their form, making it difficult to correct mistakes or proactively prevent injuries. It is crucial to address these risks early, rather than allowing athletes to continue poor form over a prolonged period of time. Left unchecked, these injuries can result in recurring pain, chronic injuries and long-lasting mobility problems including overall decreased ability to perform daily activities.

1.1 Project Proposal

Our team set out to develop an AI-powered system designed to analyze deadlift form, classify movement patterns, and provide corrective feedback to help prevent injuries. By leveraging keypoint detection models, pose estimation techniques, and machine learning algorithms, our goal is to enhance workout safety and optimize performance. This solution has the potential to expand to other exercises and improve accessibility to personalized coaching, making high-quality feedback available to lifters of all experience levels.

Our proposed AI system would allow users to upload a video of themselves performing a deadlift and receive real-time feedback. The system uses keypoint mapping to accurately analyze a user's deadlift technique, identifying deviations from a ground truth. For deadlifts specifically, this optimal form is considered maintaining a neutral spine throughout the movement, minimizing the risk of lumbar spine injuries. [3] The proposed system then provides immediate, actionable feedback to help users correct their posture and movement patterns. By addressing form issues early, the system helps mitigate injury risks and supports lifters in achieving safer and more effective training sessions.

2 RELATED WORK

Our project specifically focuses on perfecting deadlift form, drawing on the design and methodology of the following works that have explored AI-driven form analysis and pose estimation for various exercises.

2.1 Using Pose Estimation Algorithms to Build a Simple Gym Training Aid App

This article focuses on developing a simple gym training application utilizing pose estimation algorithms. Kapica demonstrates how tools like Google's MoveNet can be integrated into an app to provide real-time form correction and guidance during workouts. The article highlights the step-by-step process of setting up pose detection, overlaying keypoints on a user's body, and giving feedback based on detected movements. The solution emphasizes ease of implementation and practical usability, aiming to make fitness feedback accessible to nontechnical users. [2]

2.2 AIFit: Automatic 3D Human-Interpretable Feedback Models for Fitness Training:

AIFit introduces a sophisticated approach to providing fitness feedback using 3D pose estimation and human-interpretable models. Unlike simpler 2D methods, AIFit relies on detailed 3D skeletal reconstructions to assess exercise form, identify deviations, and offer corrective guidance. The system uses deep learning and computer vision techniques to generate automatic feedback that mirrors the insights of professional trainers. The emphasis is on high accuracy, real-time performance, and robust feedback mechanisms that adapt to various types of exercise and user body structures. [1]

2.3 Real-Time Fitness Exercise Classification and Counting from Video Frames

Riccio's work focuses on developing a system for real-time classification and repetition counting of fitness exercises. Using pose estimation frameworks, this approach identifies exercise types and counts repetitions by analyzing video frames. The solution addresses challenges related to different exercise speeds, partial occlusions, and varying user form. The system provides immediate feedback and accurate counting, making it useful for automated workout tracking and performance analysis. The paper underscores the importance of real-time processing and robust classification models for practical fitness applications. [4]

All three works address the need for accurate real-time exercise analysis using pose estimation. While Kapica's solution emphasizes simplicity and accessibility for app development, Fieraru et al. introduce a more advanced 3D model capable of offering detailed form corrections. Riccio focuses on efficient exercise classification and counting, ensuring accurate real-time feedback. Each work tackles challenges such as variability in user movements, exercise types, and the need for fast, responsive systems, offering different levels of complexity and accuracy depending on their target use case.

3 METHODOLOGY

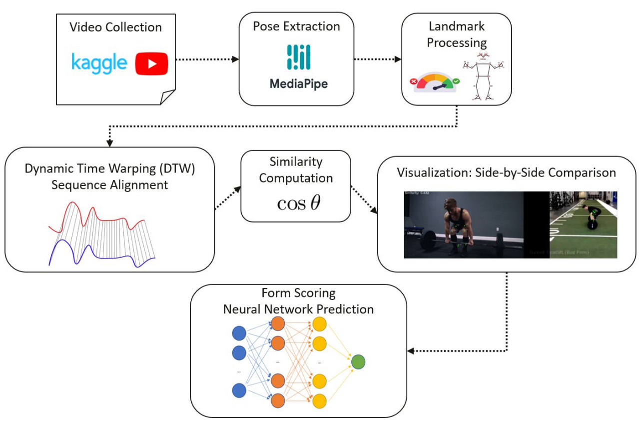

Figure 1: Workflow for Deadlift Form Analysis

3.1 Data Sources

For this analysis, we used a combination of deadlift videos sourced from YouTube and a publicly available dataset on Kaggle titled *Gym Workout Exercises Video Dataset* [5]. However, the inherent limitations of the dataset significantly constrained the accuracy and generalizability of our model. Of the approximately 100 videos analyzed, a substantial majority contained incomplete or technically flawed repetitions, with most videos demonstrating partial movements, typically starting at the top of the lift, descending partially, and returning to the starting position without executing a full proper deadlift. These data quality issues fundamentally undermined our ability to train a robust and precise form analysis model, as the training data failed to represent comprehensive, technically correct lifting techniques. Consequently, the technical integrity of our source videos emerged as the primary bottleneck in developing a high-fidelity form assessment system.

3.2 Pose Detection and Data Extraction

The system initializes the MediaPipe Pose model with a confidence threshold of 0.3 to ensure reliable detections. Key landmarks relevant to deadlift analysis, including shoulders, hips, knees, and ankles, are extracted for each frame. The `process_video` method reads video frames using OpenCV, applies the pose model, and stores the keypoint coordinates, timestamps, and confidence scores. The output is a `ProcessedSequence` containing:

- **Frames**: Image data for each frame.
- **Landmarks**: Pose keypoints (x, y, z coordinates).
- **Timestamps**: Time in milliseconds for each frame.
- **Confidence Scores**: Visibility scores for each keypoint.

It's important to note that Mediapipe landmarks do not include spine markers, which are crucial for assessing deadlift form. Without tracking spinal positioning, evaluating back alignment becomes difficult and further limits the accuracy of form analysis.

3.3 Sequence Alignment with Dynamic Time Warping (DTW)

To address differences in exercise speed, the `align_sequences` method applies DTW. A distance matrix is computed using the Euclidean distance between keypoints in each frame of the two sequences. DTW calculates the optimal warping path to align the sequences, resulting in synchronized `ProcessedSequence` objects for comparison.

3.4 Similarity Computation

The `compute_similarity` method calculates a weighted cosine similarity between the aligned sequences. Confidence scores serve as weights, emphasizing accurately detected keypoints. For each aligned frame, the method:

(1) Weighs the landmarks by confidence scores.
(2) Computes the cosine similarity between weighted landmarks.

The method returns:

- **Overall Similarity Score**: The mean of frame-level similarities.
- **Frame-by-Frame Similarity Scores**: Detailed similarities for each frame.
- **Aligned Sequences**: For further visualization and analysis.

3.5 Visualization of Comparisons

The `visualize_comparison` method generates side-by-side frames of the reference and user sequences. Keypoints and confidence scores are overlaid on the frames, and frame-level similarity scores are displayed. This visualization allowed us to identify deviations in form during specific frames.

3.6 Similarity Timeline Plotting

The `plot_similarity_timeline` method plots similarity scores over time, providing a graphical overview of the user's form relative to the reference. This allows identification of performance inconsistencies across different phases of the deadlift.

3.7 Form Analysis Workflow

The complete analysis workflow is encapsulated in the `analyze_videos` method, which:

(1) Processes the reference and user videos.
(2) Aligns the sequences using DTW.
(3) Computes the similarity scores.
(4) Generates visual feedback and plots.

4 RESULTS

Our analysis of deadlift rep detection data reveals several key findings:

4.1 Shoulder Height Over Time

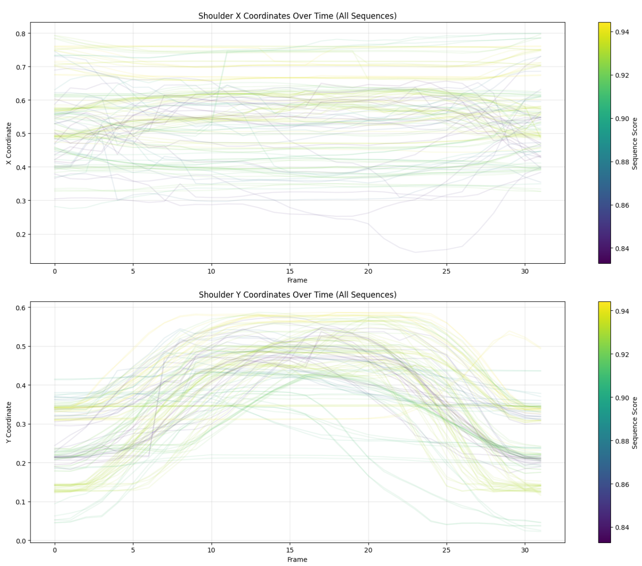

Figure 2: Shoulder height measured by coordinates over time.

The graphs pictured above show the movement of the shoulder joint over time during the exercise sequence, with the x-coordinate plot representing the horizontal position and the y-coordinate plot illustrating the vertical position. In the x-coordinate graph, the shoulder's movement forms a mostly straight pattern with varying y-intercepts, reflecting consistent horizontal back-and-forth motion. In contrast, the y-coordinate graph exhibits a distinct curve that illustrates the lifting motion characteristic of the deadlift.

4.2 Incomplete Repetitions

The majority of the ~100 video samples in the dataset contained partial or technically flawed deadlift repetitions, where the lifter would start at the top position, descend partially, and then return to the starting point without completing the full lift. This issue with the source data significantly limits the model's ability to accurately learn and detect proper deadlift form.

4.3 Noisy Slope Signals

The slope analysis plots show highly variable and noisy slope signals, even for the detected reps. This suggests that the underlying sensor data have quality issues that make it challenging to reliably identify key events like the start and end of a deadlift rep.

4.4 Limitations of Detected Reps

The "Detected Rep" signal, which should indicate when a complete repetition of the deadlift was identified, appears to have a relatively low overall magnitude compared to the other signals. This implies that the rep detection algorithm is missing a substantial number of full reps, further undermining the quality of the training data.

4.5 Training and Validation Loss

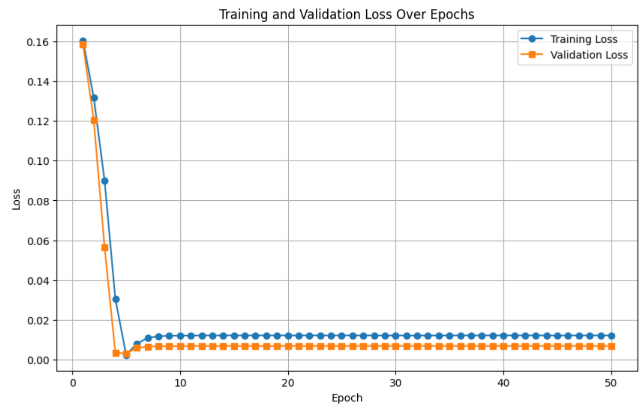

Figure 3: Training and Validation Loss Plot

The training and validation loss curves pictured above illustrate the performance of the deadlift form scoring neural network over 50 epochs. The loss decreases sharply within the first 5 epochs, indicating that the model is quickly learning to minimize the error. After epoch 5, both the training and validation losses stabilize at very low values, with the training loss converging around 0.01 and the validation loss remaining slightly lower.

This performance was achieved through careful data preprocessing, which involved manually sorting and selecting good and bad video examples to ensure high-quality training data. The close alignment between the training and validation losses highlights minimal overfitting, suggesting that the model generalizes well to unseen data. Furthermore, the smooth and consistent nature of the loss curves, without noticeable spikes or fluctuations, indicates a stable training process. This stability can be attributed to effective hyperparameter choices and the meticulous preprocessing of the dataset.

5 CONCLUSION

This project has highlighted the critical importance of high-quality training data when developing machine learning models for exercise form analysis. The dataset used in this study suffered from fundamental limitations that prevented the model from learning an accurate and generalizable representation of proper deadlift technique. Going forward, several key improvements could enhance the usability of this project:

- **Curate a New Dataset**: Curate a new dataset with a focus on capturing complete and consistent deadlift repetitions.

- **Diversify the Dataset**: Increase the number of video examples, including more diverse body types, lifting styles, and varying camera angles to bolster the model generalization for different users.
- **Explore Alternative Sensor Metrics**: Integrating additional biomechanical measurements like joint angles, velocities, and forces could provide a richer set of features for the model to learn from.
- **Injury Risk Prediction**: Enhance the model to predict potential injury risks based on detected poor form, providing proactive recommendations to avoid injuries.
- **3D Pose Estimation**: Incorporate 3D pose estimation models to improve the accuracy of landmark detection, especially for movements that involve depth variations.

In summary, the inherent limitations of the dataset - dominated by incomplete lift examples and noisy sensor signals - have created significant constraints on the model's ability to accurately detect proper deadlift form. Improving the quality and representativeness of the training data would be a crucial next step in developing a more robust exercise form assessment system. One key advantage of this pipeline is the overall flexibility. By swapping the training data and target landmarks, the same approach could be used to train models for analyzing other exercises, such as squats or bench presses. This adaptability allows for broader applications, quicker implementation and enhanced extensibility.

REFERENCES

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A OVERFLOW

A.1 Deadlift Rep Detection and Slope Analysis

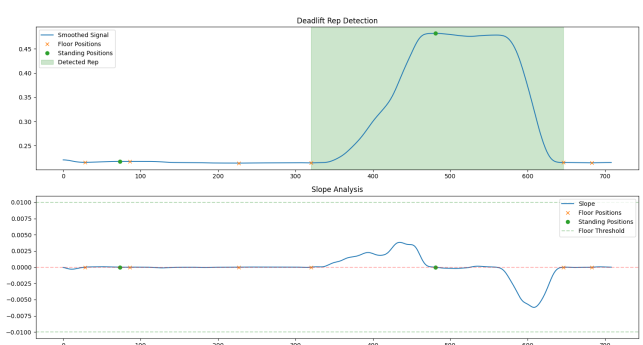

Figure 4: Video Example 1

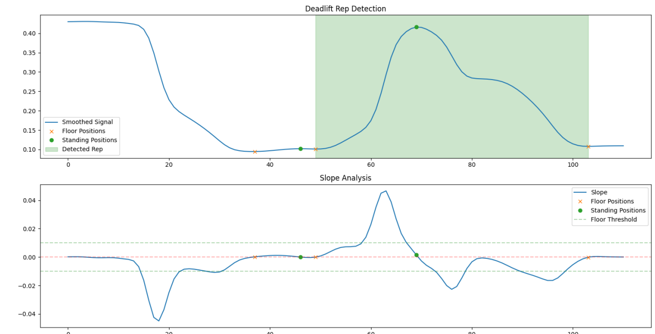

Figure 5: Video Example 2

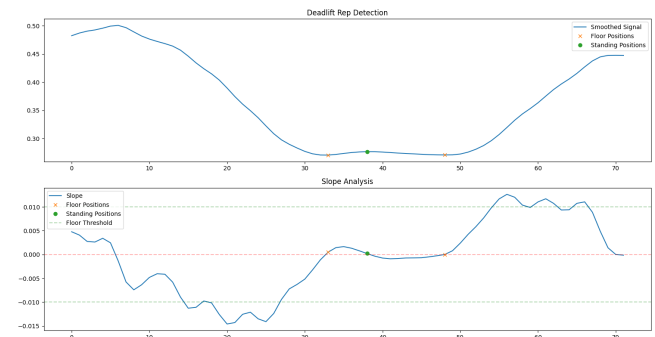

Figure 6: Video Example 3

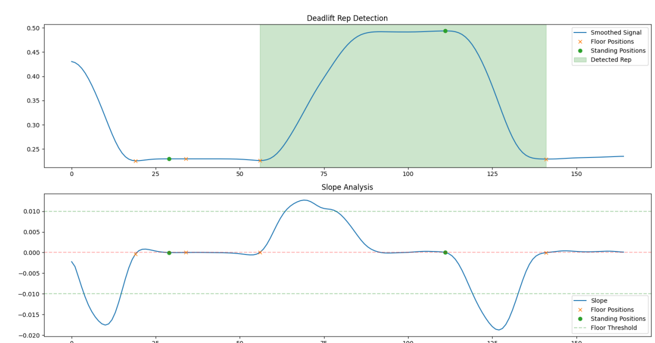

Figure 7: Video Example 4

A.2 Keypoint Mapping and Frame Scoring

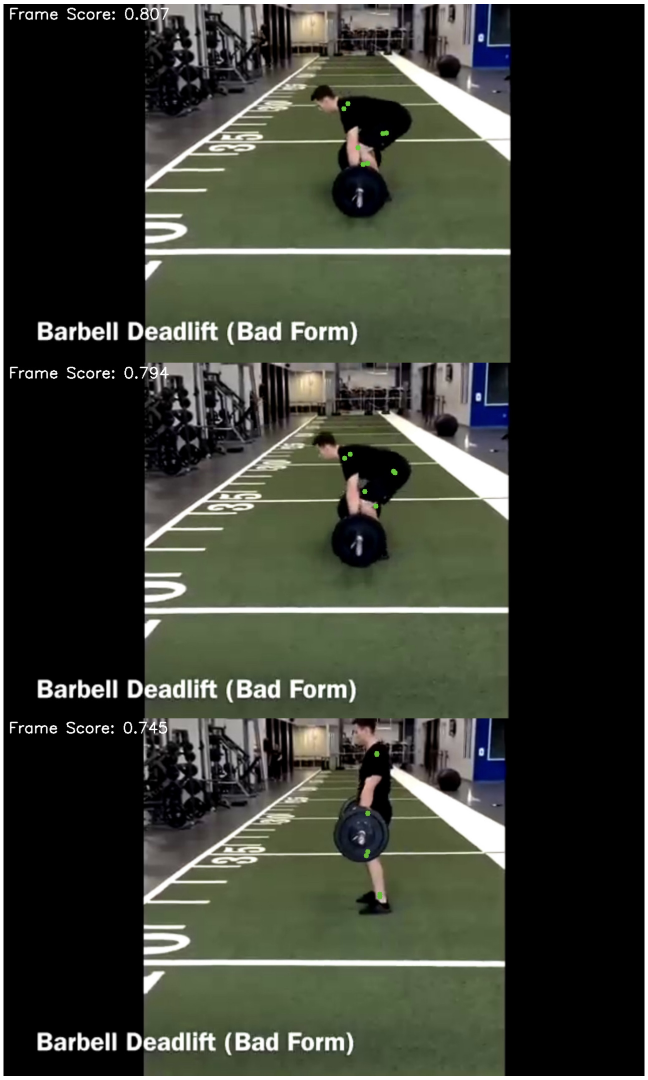

Figure 8: Frame Score (Bad Form)

Figure 9: Frame Score (Side Angle)

Cover Page

Google Colab:
https://colab.research.google.com/drive/1XeBd8rMOjCcxSKROFr0s38-nuKYtwev9?usp=sharing

Slide Presentation:
https://docs.google.com/presentation/d/1jVd7iC-9-NjNMepjdpbR6jMBCs82Q7aHLt7VCoUzBVg/edit?usp=sharing

Video:
https://utexas.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=3870fc08-c821-4542-8c54-b246002c621b