Analyzing Deadlift Form with Bio-mechanical Linkage Data

Eric Gilerson, Nikhil Lazarro, Ishaan Puri, Razin Farooqi

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Contact Information:

Eric Gilerson: ericgilerson@gmail.com

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Abstract

This study explores an approach for analyzing deadlift forms using biomechanical linkage data and neural networks. Methods such as personal trainers and manual corrections can be costly and ineffective without the right tools, creating significant injury risks. By using Openpose pose estimation and feed-forward neural networks to classify deadlift form and deviations from proper form, we developed a system that has nearly 100% accuracy. Because these results are often hard to understand, a custom GPT was created to transform the data to be readable for people to take action and fix their form. The approach demonstrates the effectiveness of machine learning and pose estimation working together in strength training and proves how it can be used in many other applications of exercise.

1 Introduction

1.1 Background on Deadlift and its Importance

The deadlift is a fundamental exercise in strength training that engages multiple muscle groups, including the hamstrings, glutes, lower back, and core. It is a critical component of powerlifting and is often included in strength and conditioning programs due to its effectiveness in building overall body strength and functional fitness. The deadlift mimics real-life movements such as lifting heavy objects from the ground, making it not only beneficial for athletic performance but also for everyday activities. Proper execution of

[0]Source code to recreate our results is available at: GitHub Repository Link

the deadlift can enhance muscle development, improve posture, and increase bone density, which is particularly important for preventing osteoporosis (Escamilla et al., 2000; McGuigan & Wilson, 1996).

1.2 Challenges in Correcting Deadlift Form

Despite its benefits, the deadlift poses significant risks if performed using improper form. Common errors include excessive rounding of the back, improper knee alignment, and incorrect hip positioning, which can lead to serious injuries such as herniated discs and muscle strains. The lumbar spine is particularly vulnerable, with incorrect form increasing shear and compression forces on the lumbosacral disc (L5/S1) (Sutthiprapa et al., 2017). Traditional methods of form correction involve manual intervention by a trained professional, which can be costly and not always accessible. Furthermore, self-assessment using mirrors can be unreliable and may not capture all angles necessary for comprehensive form analysis (Dempsey et al., 2014).

1.3 Objectives of the Study

The primary objective of this study is to develop a scalable and accessible method for analyzing and correcting deadlift forms using advanced technologies. Specifically, the study aims to:

1. Utilize biomechanical linkage data derived from video recordings to create a detailed analysis of deadlift form.
2. Develop a feed-forward neural network that can classify proper and improper deadlift forms based on the biomechanical data.
3. Develop a feed-forward neural network that can tell deviations from proper form based on the biomechanical data.
4. Integrate a custom GPT model to provide actionable feedback and recommendations for correcting form issues.
5. Validate the effectiveness of the proposed system in accurately identifying and correcting deadlift form errors.

By using technologies such as OpenPose for pose estimation and neural networks for data analysis, this study seeks to provide an innovative solution that can be widely adopted in various settings, from personal training to rehabilitation clinics. The ultimate goal is to enhance the safety and effectiveness of strength training by reducing the risk of injury associated with improper deadlift form.

2 Literature Review

2.1 Introduction

The deadlift is a fundamental exercise in strength training, but it poses significant risks of injury if performed with improper form. Traditional methods for analyzing exercise forms involve costly and complex equipment. Recent advancements in computer vision and machine learning offer new, more accessible ways to evaluate and improve exercise techniques. This literature review explores current research on deadlift form analysis, the application of biomechanical models, and the use of neural networks for posture classification.

2.2 Deadlift Form Analysis

Proper deadlift form is crucial to prevent injuries, particularly to the lower back. Incorrect form can lead to increased shear and compression forces on the lumbar spine, increasing the risk of herniated discs (Sutthiprapa et al., 2017). Studies have shown that common errors include excessive rounding of the back and improper knee alignment, which increase the stress on the lumbar region (Escamilla et al., 2000; McGuigan & Wilson, 1996).

2.3 Biomechanics in Exercise Training

Biomechanical analysis provides detailed insights into the movements and forces involved in exercises. Traditional methods such as motion capture systems and force plates offer high precision but are expensive and impractical for widespread use (Dempsey et al., 2014). Recent advancements in technology, such as the Microsoft Kinect, enable more accessible motion analysis. For example, Sutthiprapa et al. (2017) utilized Kinect for real-time detection of deadlift form, calculating compression and shear forces on the lumbosacral disc using Chaffin's biomechanical model.

2.4 Neural Networks in Form Assessment

Neural networks, particularly feed-forward neural networks, have been increasingly applied to exercise form analysis. Unlike convolutional neural networks typically used for image recognition, feed-forward neural networks can effectively process biomechanical linkage data derived from videos. Our project leverages this approach by extracting 18 key points on the body every five frames from deadlift videos and feeding this data into the neural network to classify form accuracy. This method has proven effective in distinguishing between proper and improper form (Kim et al., 2020).

2.5 Applications and Comparisons

The use of OpenPose for real-time human pose estimation has been instrumental in our project. Cao et al. (2017) demonstrated the capability of OpenPose to accurately detect human body key points, which we adapted for deadlift analysis. Additionally, research by Taborri et al. (2021) highlights the integration of biomechanical data with machine learning algorithms to improve posture classification accuracy.

2.6 Gaps and Future Directions

Despite the advancements, there remain gaps in the current research. Most studies focus on static analysis and do not account for dynamic variations in form throughout the exercise. Furthermore, scalable solutions for real-world implementation are limited. Our project addresses these gaps by using biomechanical linkage data and a feed-forward neural network, providing a scalable solution for deadlift form analysis.

The integration of biomechanics and neural networks offers a promising approach to improving exercise form analysis. Our project builds on existing research by developing a novel method for analyzing deadlift form using biomechanical linkage data, contributing to the advancement of exercise science and injury prevention.

3 Methodology

3.1 Data Collection

To train a model on proper deadlift form, a large video dataset of deadlifts was needed, including both good-form and bad-form deadlifts. Video data was collected from three angles starting with facing the deadlift, moving clockwise: 0 degrees, 30-60 degrees, and 90 degrees to ensure that the model understood all patterns of good and bad form which might not be in a different angle. Multiple rounds of data collection were necessary to provide a large enough dataset for a well-performing neural network. An initial round of deadlift form data was collected from online sources. These include datasets from Kaggle as well as fitness training videos on YouTube. As part of the training and evaluation set, Razin Farooqi was filmed performing deadlifts with both good and bad form. The data was used to train and evaluate the network after preprocessing. All video data was converted to the proper .MP4 format in H.264 encoding to ensure consistent results. Each deadlift video was labeled corresponding to its form(good or bad) and the angle at which the video was taken.

3.2 Linkage Code Development

As models trained on video can be inconsistent due to many factors such as background noise, different body types, and significant amounts of unnecessary information, the videos used were preprocessed before training or evaluating the neural network. The way that this was done was by using biomechanical linkage diagrams or "pose estimation" to connect joints and body features that can be identified in the video. This approach allowed the model to classify the quality of a lift accurately, as a good lift is defined by the proper alignment and load distribution across the joints.

The linkage script identified 18 key points on the body for every fifth frame of the video. To ensure the accuracy of these key points, the script uses a smoothing window that averages the data across five frames, reducing noise and providing a smoother estimation of the points throughout the video. Without this averaging, the pose estimation will not be consistent and there would not be a pattern that the neural network can learn from.

The output of this script is a JSON file that contains the coordinates of each of these key points for each frame calculated, as well as a video of the skeleton connecting the key points from the JSON file to visually see the results of the pose estimation. This video allows us to verify and select sufficiently accurate pose estimations, as the smoothing process and calculations do not always produce perfect results.

During pre-processing, the pose estimation sometimes generates null values in frames where there is not enough information to identify a key point. These null values are then replaced with the placeholder [-1,-1], ensuring that they will not negatively impact the neural network during training or produce errors due to null values.

Through this processing, the data is stripped of all other unnecessary extra information in the videos and ensured through the ability to see the linkage output that the video will be reliable data to train off of. This increases not only the effectiveness of the model but also the efficiency as the data is tailored to only the model.

3.3 Neural Network Training

This project uses two different neural networks: one for the classification of form as either “good” or “bad”, and another, the deviation model, which provides feedback on how much the key points/nodes from the pose estimation deviate from what the model can predict as a proper form, excluding the [-1, -1] placeholder values to not influence the rest of the predictions by these low and unknown values. For the neural network to train, the input data must be preprocessed once more, flattening the 2D coordinates (x and y coordinates from the JSON pose estimation) of each frame into a 1D array. The network still understands that these values represent specific points on the body, preserving the relationships the coordinates have. This allows the model to recognize the patterns for “good” form deadlifts, making it possible to generalize to new data with accurate analysis and classification.

The classification model is a sequential neural network with three layers, comprising 128, 64, and 32 neurons respectively. Each layer uses batch normalization to improve the stability of the training process and a 50% dropout rate to prevent overfitting on the training data.

The activation function used for all the layers in both models is leakyReLU with an alpha of 0.01. This function creates a small(due to the alpha of 0.01), non-zero gradient even when the neuron is not active, which has a specific use in this scenario, as it helps the network train around the placeholder values of [-1,-1] without ”killing” the neuron. By keeping the neuron active, the weights can be updated, generalizing the training set possible, even with the placeholders. For the output layer, a sigmoid function is used to classify the input as good or bad form and to provide a confidence level for each prediction. The sigmoid function is used because it has a range of [0,1], and only approaches these values, perfect for giving a confidence level and classification as the model can never be 100% confident. The binary cross entropy loss function is used for the classification model which is standard for binary classification outputs such as this.

We experimented with multiple architectures for the deviation model before settling on a 2D convolutional model followed by dense layers. The other architectures included: a simple dense model, a 2D to 1D convolutional model, an LSTM model, an Attention model, a Transformer Model, and a 3D model; All of these models were not able to accurately identify deviations in the evaluation set and gave similar deviations for good and bad form data. These would not have been accurate models, giving poor results, but the 2D convolutional model was. The final architecture consisted of seven layers, with 2D convolutional layers progressing from 64, 128, 256, to 512 filters, followed by dense layers with 512, 216, and 128 neurons. This model structure, trained with a batch size of 32 over 750 epochs, was chosen for its ability to perform well against the evaluation set while the others did not. This architecture allows the model to understand the temporal relationships in the data through the dense layers, as these layers process the data as a whole, while better predicting the deviation of the pose through the 2D convolutional layers as the pose was rendered in 2D, making it possible to recognize the patterns in a 2D space.

In the deviation model, L2 regularization was used in each layer, with a penalty of 0.01, as well as a 50% dropout rate, similar to the classification model. Both of these changes between layers minimized the risk of overfitting and allowed for more accurate generalization. A custom loss function was used for the deviation model, which excluded the placeholder values from the loss function in the training to avoid skewing the model's predictions. This is important because trying to predict values that were never there in the first place can lead to other values being inaccurate due to the fact the model trains as a whole, frame by frame, not point by point. After masking the placeholder values, the loss function computed the Euclidean distance per point, focusing the model's learning on the true deviations in the form data.

The deviation model was only trained on data representing good form.

This was done based on initial experiments where training on both good and bad form data led to less distinguishable between the 2 results on the evaluation set. By focusing only on good-form data, the model was better able to identify and quantify deviations where bad form deviated more than predicted from good-form data.

Both models used a step decay learning rate reducer. This decreased the learning rate by 20% every 25 epochs and allowed the models to converge effectively by creating smaller and more concentrated updates as training progressed through the epochs.

4 Implementation

4.1 Tools and Packages Used

For the pose estimation, the script uses the OpenCV package to load the OpenPose model. By loading the pose_deploy_linevec.prototxt file, the neural network architecture was processed including the layer connections and the overall model structure, then the pose_iter_440000.caffemodel was loaded which included the weights to this neural network. This combination made it possible for the detection of key points through the OpenPose packages. Additionally, OpenCV was used to complete this pose estimation using a GPU, outputting more accurate and efficient results with fewer mistakes than a CPU would produce.

For the neural network, TensorFlow and Keras were used to build the sequential models and all of their features. These packages also allowed for the models to be tested and saved efficiently for further use.

OpenAI was then used to create a custom GPT, Deadlift Keypoint Analysis, which takes in the output of the deviation model suggestions and explains, in words, suggestions to better deadlift form based on each keypoint deviation in order of importance.

4.2 Detailed Steps

Data is first collected through online sources with already labeled data to not make mistakes when labeling. These sources can include datasets found on Kaggle and similar websites as well as searching social media platforms including fitness influencers who show both proper and improper form. Then data can be collected in the gym who are trained and experienced in the deadlift and can give good and bad form data. It is also recommended to get about two times the amount of data that one accounts for as the pose estimation could not work well for a large portion of data.

Then these videos all are converted to the same codec, in this case, it is .mp4/H.264 and preprocessed through the pose estimation. Each of these videos then needs to be manually checked if the pose estimation worked and if no noise/points are moving where they do not belong.

Once the videos with acceptable pose estimations are identified, the corresponding JSON files containing the key points for each frame are fed into the classification neural network and then the deviation neural network. After the training is finished, the models are evaluated on the unseen dataset. If the results are not as expected, tune the hyperparameters or the model structure and retrain. Then repeat this process until the results are as expected.

Then use the results from the deviation and classification model and input them into the custom GPT, Deadlift Keypoint Analysis, to get personalized advice that will improve the deadlift.

Through our model and dataset, this process was achieved with very favorable results.

5 Results

5.1 Model Accuracy and Performance

To capture the accuracy of the classifier network, the binary cross entropy loss function converged, with some spikes about every 100 epochs, to very close to 0 giving a 100% classification accuracy on the last epoch on the test data set as well as converging to very close to 100% accuracy which was measured frame by frame not by each video. This was also apparent in the evaluation set as this network was able to accurately identify all of the unseen data as good or bad form throughout or only in certain parts of the movement, which is consistent with what we identified in the videos. Figure 1, the Loss and Accuracy graphs are shown below.

For the deviation model, after experimenting with multiple different networks that did not have consistent and well-performing results, we landed on the 2d convolutional network which was able to produce consistent and accurate results. Because the deviation model was predicting points, the

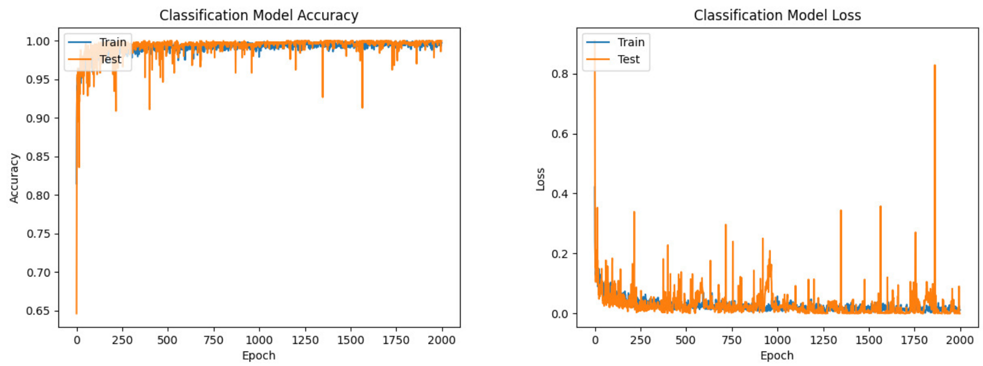

Figure 1: Loss and accuracy graphs for the classification model.

model used an Euclidean loss function as well as a Mean Absolute Error to understand how well the model performs on the test set. These metrics also converged showing that the model was able to well predict and understand the points needed for a good form deadlift, and this was also apparent as there were consistently higher deviations in the evaluation dataset for bad form than good form. Figure 2, the Loss and Error graphs are shown below.

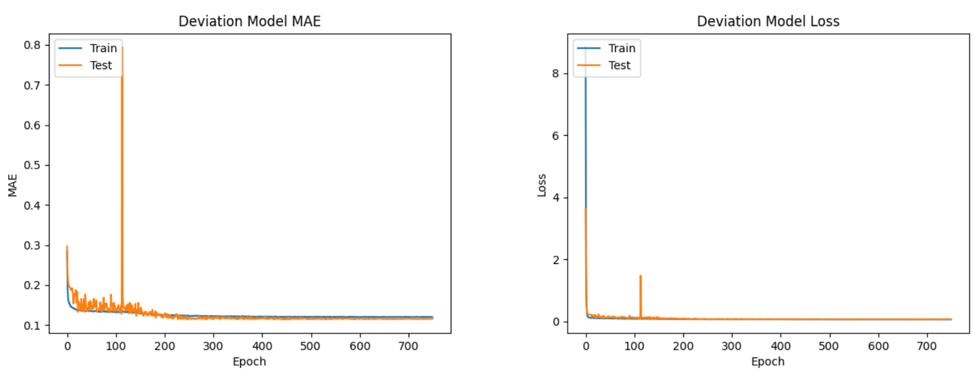

Figure 2: Loss and error graphs for the deviation model.

Not only was it important to have a well-rounded architecture for these models to perform well, but the reduced step learning rate was essential to allow the model to converge. This was also especially important for the deviation model as the reduced learning rate allowed it to pick up on small patterns in the good form data not in the bad form, making the model more accurate. Shown below in Figure 3 are 3 different snippets of examples of this output which are all verified to be accurate.

5.2 Custom GPT Analysis

Even though our model provides accurate numerical data for various actions, more than this data needs to be interpreted. To fix this issue, we created a tool to translate this numerical information into words in a way that anyone with a basic understanding of the body can understand

Large language models, such as GPTs, are not only useful for generating text but also can be an intermediate step between different systems or protocols as they can understand both as similar tokens giving a result that is what the model means, translating the data. Recognizing this potential, we developed a custom GPT from OpenAI to interpret our model's output based on the inputs of what each key point aligns to. This GPT can understand and provide clear, user-friendly feedback on any adjustments that are needed, giving the most important ones(highest deviations) first.

The custom GPT analyzes the numerical data generated by our deviation model's predictions, correlates key points to the given specific body parts, and assesses how these key points should be adjusted for correct alignment. It then generates straightforward recommendations, indicating what changes they should make to ensure that all key points are accurate to make a proper deadlift.

Because the model does not give a direction of the key point deviation, the GPT could give an inaccurate result, but based on many trials, it will correct itself by looking at the rest of the deviations, not just one point.

This approach of using GPTs as a translation tool is relatively new and not very widespread but has proven to be highly effective. By transforming complex numerical data into clear, helpful improvements, our method makes it possible for people to not only know where their deadlift is wrong, but how to improve on it.

Figure 4 illustrates how the GPT provides feedback on necessary changes.

6 Discussion

6.1 Interpretation of Results

The success of the frame-by-frame system of analyzing deadlift form allows this model to understand both where and when the deadlifter has errors in their form. Repeated rounds of training eventually refined the model's ability to analyze deadlift form and give feedback at multiple frames during the deadlift. It is important to give specific recommendations at all necessary stages of the compound lift in order to best assist weightlifters in improving lifting form. The overall model created in this project successfully determined accurate deadlift form from inputted data. Refining the neural network resulted in final tests outputting nearly 100% accuracy by the last epoch of the test data, highlighting the significance of the model's performance. Additionally, measuring frame-by-frame deadlift form data showed a near-100% accuracy by the last epoch of test data, further illustrating the model's accuracy in determining proper form throughout the video.

The integration and coaction of neural networks, linkage diagram conversion, and an analysis GPT model allowed for the compression and expansion of data to create an accurate model with human language inputs and outputs. Changes in code and model inputs were needed to accommodate multiple types of data files throughout the model, especially when bridging data between model components. Multiple rounds of testing and refinement during the research process aided in the cohesion and unity of the model's components. This was a critical step in creating an accurate model that retains necessary data throughout and thus allowed for smooth transitions with corresponding file inputs and outputs.

Cohesion between the model's components was especially important when developing the custom GPT function. After multiple rounds of testing and data training, the custom GPT proved successful in translating numerical data point adjustments into human language, highlighting the overall model's potential to streamline user interaction with the model. Despite a lack of previous implementations of ChatGPT as a translation tool, building a custom GPT was an appropriate method of translation from computer-generated numbers to human feedback. Utilization of accurate AI models in an increasingly AI-driven society is beneficial when implemented correctly, such as for translation in small-scale models. The success of the custom GPT directly satisfied the need to output suggestions in a human language format, thus allowing the overall model to expand future implications to public use of the model.

6.2 Implications for Exercise Training

The capability to analyze deadlift form from a user video input provides weightlifters with a simple way to receive feedback on lifting form, thus making this model a useful tool for athletes, weightlifters, and other fitness individuals. As stated earlier, the high accuracy rate of this model justifies the benefit of the model in exercise training. The model has the potential to refine smaller aspects of the form of experienced weightlifters.

Furthermore, the accuracy of a step-by-step model may even notice what weightlifting coaches would not. Small form adjustments can have large impacts on muscle strain when deadlifting, and thus the model's precision and accuracy can advise minor changes in form that a weightlifting coach has not corrected. In addition, this model can assess individuals that weightlifting coaches do not, such as individuals without access to coaches or those who workout at home. A model like this expands access to high-quality training and thus can help promote fitness and form consistency for long-term gains.

Since the model analyzes the movement of specific joint linkage points, the model is able to detect subtle deviations from proper lifting form and thus can detect small improvements in lifting form. The model has the potential to analyze deadlift form and analyze changes in a person's lifting form over a period of time. Improvements and further suggestions can be given to the weightlifter, which illustrates the ability to adapt to the weightlifter and personalize goals based on needed form improvements.

6.3 Potential for Other Exercises/Action

Our approach in creating this model, which produced very strong results for the deadlift, can be used for multiple other actions involving joint movement. There are four steps of development to follow when creating a model for an alternative action. Firstly, an action involving joint movement must be identified, and data must be available either through research or data creation and collection. Collect data on proper and improper form, as well as from multiple video angles for various perspectives on the targeted joint movement. Secondly, create a pose estimation model that identifies the targeted joint movements and pulls only that data to generate a linkage diagram.

Identifying key movements using a linkage diagram not only allows a model to analyze proper form better, but it also compresses large video data files that carry unnecessary information and takes up excessive storage in many applications. Once a pose estimation model is complete, two neural networks will be developed, one for the classification of proper and improper form and another for the deviation of improper form. Develop these neural networks by feeding in training data, rewriting code, and restructuring the architecture until the model reaches a very high level of accuracy. Lastly, a Large Language Model such as a custom GPT should be developed to understand the model's numerical output. The GPT should output analysis in a human-readable format, allowing users to understand the results and suggestions made by the model. The model's components must be streamlined with one another, as this will allow for the retention of critical data and provide the most accurate result of form analysis. This step-by-step development process resulted in an accurate model that fulfilled an intended purpose to a high degree, and thus may likely prove sufficient when designing other similar models.

Our model, having been trained off of pose estimation data, can be generalized to other actions, allowing it to be applied to various physical activities. Gym exercises including squats and bench presses would be the early stages of expanding this model, and a more advanced version of this model could be used to analyze different sports movements. With the right amount of training and high-quality data, this skeleton can evaluate tennis strokes, basketball shooting techniques, and other dynamic actions with high accuracy, as we found with the complex example of the deadlift. This versatility makes this approach applicable to various movements, allowing for improving athletic performance in many sports.

Figure 5 shows the steps to create our deadlift model and how it can be generalized to any other movement.

6.4 Challenges Faced

The most apparent challenge during this process is the pose estimation/linkage data. OpenPose is an open-source platform that is not built for exercises which has more complications than most pose estimation needs. For example, it would be important to be able to track the person as well as the bar in the movement as there could be signs of improper form in the bar movement such as swaying and tilting. Because of these reasons, the OpenPose was not able to work properly every time and this led to losing about 30-40% of the data, so to make a better and more accurate model that could be used for all data, the most important step would be to make a specialized pose estimation model for the exercise. This would also eliminate the need for placeholders which would make the model even more accurate.

Another issue on top of losing data due to bad pose estimation was not finding enough reliable data. For a good model to work that would apply to all types of body types in people and filming angles, a significant amount of more data would need to be found or collected to create a more general model that would perform better on all types of people.

With this extra and better-suited data, a more complex model would be needed as well as higher-performing GPUs to ensure that the training process can function smoothly and without mistakes.

If these challenges are all able to be overcome an incredibly-performing model can be created that can be used by everyone and can be commercialized to help many people not have injuries and increase the progress of their fitness journey.

7 Future Work

7.1 Expanding to an Application

A future application of this project would be to implement this functionality of classifying and improving deadlift form into a smartphone app. This can include user-friendly interfaces and step-by-step guides to improve deadlifts which can help fulfill the role of fitness coaches as they are not always fully necessary or affordable when implemented into an app for everyday lifters. The app would combine a linkage diagram generator, the neural network algorithm, and a large language model such as ChatGPT to process deadlift videos and provide the user with human language instructions on improving deadlift form at individual points in time.

Since all video data was converted to linkage diagrams, file sizes have been condensed, and thus minimal storage space would be needed for this application which would improve the efficiency of the program as well. The use of multiple video angles within the training data can allow users to film video from multiple angles while still getting accurate results from the neural network. This eliminates the need for specific setup guidelines when videoing, and thus further promotes a more user-friendly experience. Additionally, video data from users could be used to generate linkage diagrams for further training data into the neural network. This would further increase the accuracy of the model, as a larger dataset is likely to increase the performance of the pose estimation algorithm and the suggested neural network. The development of a smartphone application using this model would prove beneficial to many lifters, athletes, and fitness enthusiasts who require supplemental coaching to improve weightlifting performance. Multiple rounds of testing and data input show increasing accuracy of this model, and thus the model is likely to perform well when used by the general population.

7.2 Extending the Model to Other Exercises

While the deadlift is widely considered to be one of the most prominent types of exercises in weightlifting, other compound lifts, including bench presses and squats, target other muscle groups that are necessary for proper balance of muscle training. Hence, another future development of this project could focus on generating similar models for other compound lifts. These lifts may include the bench press, squat, pull-up, shoulder press, and other major lifting exercises. Future models could target exercises with the highest risk of improper form such as this does with the deadlift, as these exercises likely require more in-depth coaching for newer and common weightlifters to master the lift without injuring themselves.

When collecting data for alternative exercises, a similar data-collection method would be implemented, including collecting data from multiple angles of the lift. Multiple rounds of data collection would be required, especially for exercises with multiple moving joint elements and high stress on these joints. Additionally, smartphone applications targeting accurate forms for these alternative lifts can make this model more accessible to users. The accuracy of the deadlift form model in the project proves the ability to develop other models that can accurately determine the proper form in other exercises and movements. An expansion of this project to other lifts would allow more users to analyze more lifts when lifting coaches may not be easily available.

8 Conclusion

This study of analyzing deadlift form using biomechanical linkage data and neural networks is a new and scalable approach that can evolve into a beneficial product for people who exercise. Demonstrated by the high degree of accuracy in our models through the extracted key points and the custom GPT to understand the results, using machine learning techniques and Openpose can be an effective way to assess exercises. The nearly 100% classification accuracy and high deviation accuracy of these models show their potential in weightlifting form detection and correction. Also, for a tool such as this one accessibility is crucial because it allows individuals to monitor and improve their lifting techniques without costly interventions like personal trainers.

Looking ahead, the methodology used in this model can be extended to other exercises such as other lifting movements and sports training. Our approach indicates that, with sufficient training data, it could be adapted to a wide variety of sports and fitness activities, provide real-time, accurate feedback on movement patterns, and reduce training-related injuries.

Overall, this project represents a significant advancement in biomechanics and machine learning; a solution to a critical problem in strength training and rehabilitation.

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9 Appendix

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Feedback for frame 0 in file Anglegoodform1.json:      Frame 0: Good Form (99.9993%)
Feedback for frame 1 in file Anglegoodform1.json:      Frame 1: Good Form (99.9985%)
Feedback for frame 2 in file Anglegoodform1.json:      Frame 2: Good Form (99.9982%)
Feedback for frame 3 in file Anglegoodform1.json:      Frame 3: Good Form (99.998%)
Feedback for frame 4 in file Anglegoodform1.json:      Frame 4: Good Form (99.998%)
Feedback for frame 5 in file Anglegoodform1.json:      Frame 5: Good Form (99.9977%)
Feedback for frame 6 in file Anglegoodform1.json:      Frame 6: Good Form (99.9982%)
Feedback for frame 7 in file Anglegoodform1.json:      Frame 7: Good Form (99.998%)
Feedback for frame 8 in file Anglegoodform1.json:      Frame 8: Good Form (99.9974%)
Feedback for frame 9 in file Anglegoodform1.json:      Frame 9: Good Form (99.9963%)
Feedback for frame 10 in file Anglegoodform1.json:     Frame 10: Good Form (99.9936%)
Feedback for frame 0 in file Bad23.json:       Frame 0: Bad Form (0.0%), Suggestions:
Feedback for frame 1 in file Bad23.json:       Frame 1: Bad Form (0.0%), Suggestions:
Feedback for frame 2 in file Bad23.json:       Frame 2: Bad Form (0.0007%), Suggestion
Feedback for frame 3 in file Bad23.json:       Frame 3: Bad Form (0.0003%), Suggestion
Feedback for frame 4 in file Bad23.json:       Frame 4: Bad Form (0.0001%), Suggestion
Feedback for frame 5 in file Bad23.json:       Frame 5: Bad Form (0.0%), Suggestions:
Feedback for frame 6 in file Bad23.json:       Frame 6: Bad Form (0.0%), Suggestions:
Feedback for frame 7 in file Bad23.json:       Frame 7: Bad Form (0.0%), Suggestions:
Feedback for frame 8 in file Bad23.json:       Frame 8: Bad Form (0.0%), Suggestions:
Feedback for frame 9 in file Bad23.json:       Frame 9: Bad Form (0.0%), Suggestions:
Feedback for frame 10 in file Bad23.json:      Frame 10: Bad Form (0.0%), Suggestions:
Feedback for frame 28 in file Bad27.json:   Frame 28: Bad Form (0.0009%), Suggestions:
Feedback for frame 29 in file Bad27.json:   Frame 29: Bad Form (0.0033%), Suggestions:
Feedback for frame 30 in file Bad27.json:   Frame 30: Bad Form (0.0269%), Suggestions:
Feedback for frame 31 in file Bad27.json:   Frame 31: Bad Form (0.2521%), Suggestions:
Feedback for frame 32 in file Bad27.json:   Frame 32: Bad Form (9.3707%), Suggestions:
Feedback for frame 33 in file Bad27.json:   Frame 33: Good Form (69.6714%)
Feedback for frame 34 in file Bad27.json:   Frame 34: Good Form (75.2074%)
Feedback for frame 35 in file Bad27.json:   Frame 35: Good Form (81.1286%)
Feedback for frame 36 in file Bad27.json:   Frame 36: Good Form (79.31%)
Feedback for frame 37 in file Bad27.json:   Frame 37: Bad Form (44.6572%), Suggestions
Feedback for frame 38 in file Bad27.json:   Frame 38: Bad Form (2.2321%), Suggestions:
```

Figure 3: Comparison of model outputs illustrating three different scenarios: (1) correct deadlift form, (2) incorrect form, and (3) mixed form with both correct and incorrect elements.

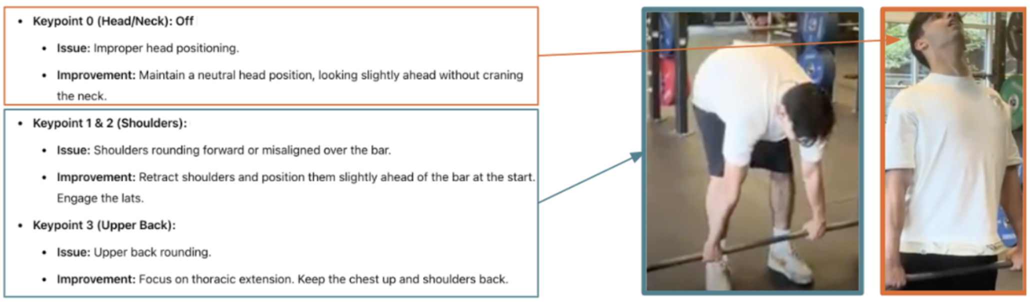

Figure 4: Example of feedback provided by the custom GPT model.

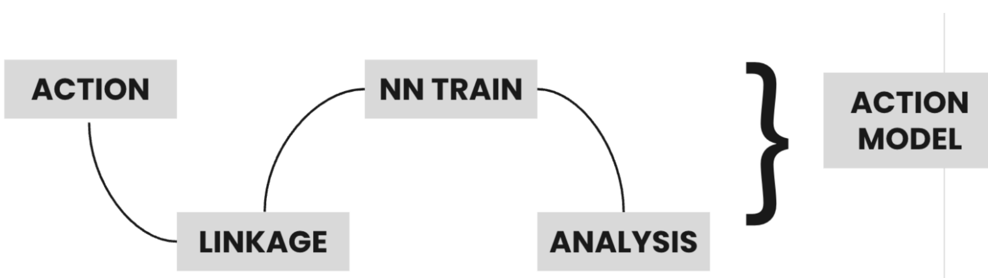

Figure 5: Diagram of the general model for other movements.